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Article (Accepted Version)

Dubinsky, Andrew, Johannes, Michael, Kaeck, Andreas and Seeger, Norman J (2019) Option pricing of earnings announcement risks. Review of Financial Studies, 32 (2). pp. 646-687. ISSN 0893-9454

Option Pricing of Earnings Announcement Risks

Andrew Dubinsky[‡] **Michael Johannes**[*] **Andreas Kaeck**[§] **Norman J. Seeger**[†]

Abstract. This paper uses option prices to learn about the equity price uncertainty surrounding information released on earnings announcement dates. To do this, we introduce reduced-form models and estimators to separate price uncertainty regarding earnings announcements from normal day-to-day volatility. Empirically, we find strong support for the importance of earnings announcements. We find that the anticipated price uncertainty is quantitatively large, varies across time, and is informative about the future return volatility. Finally, we quantify the impact of earnings announcements on formal option pricing models.

Key words: Earnings announcements, anticipated uncertainty, equity options, implied volatility

JEL: G12; G15; C53

[‡]Andrew Dubinsky is currently with Goldman, Sachs & Co. E-mail: Andrew.Dubinsky@gs.com, The views are those of the authors and do not necessarily reflect the position of Goldman, Sachs & Co.

[*]Corresponding author. Graduate School of Business, Columbia University, E-mail: mj335@columbia.edu

[§]Finance Group, University of Sussex, United Kingdom, E-mail: a.kaeck@sussex.ac.uk

[†]VU University Amsterdam, The Netherlands, E-mail: n.j.seeger@vu.nl

1 Introduction

Every quarter, the SEC requires public corporations to disclose a range of fundamental information via "earnings announcements." These information releases are arguably the primary conduit for corporate communication to investors and often generate dramatic equity price movements as prices quickly impound new information. As an example, almost 20% of Google's total equity price volatility occurs on the four days following earnings releases. Large literatures model earnings, study the theoretical pricing of earnings risks and the ex-post response of equity prices to the information releases, both contemporaneously (earnings response coefficients) and with lags (e.g., post earnings announcement drift). Overall, earnings announcements and risks are key events driving equity returns and prices.

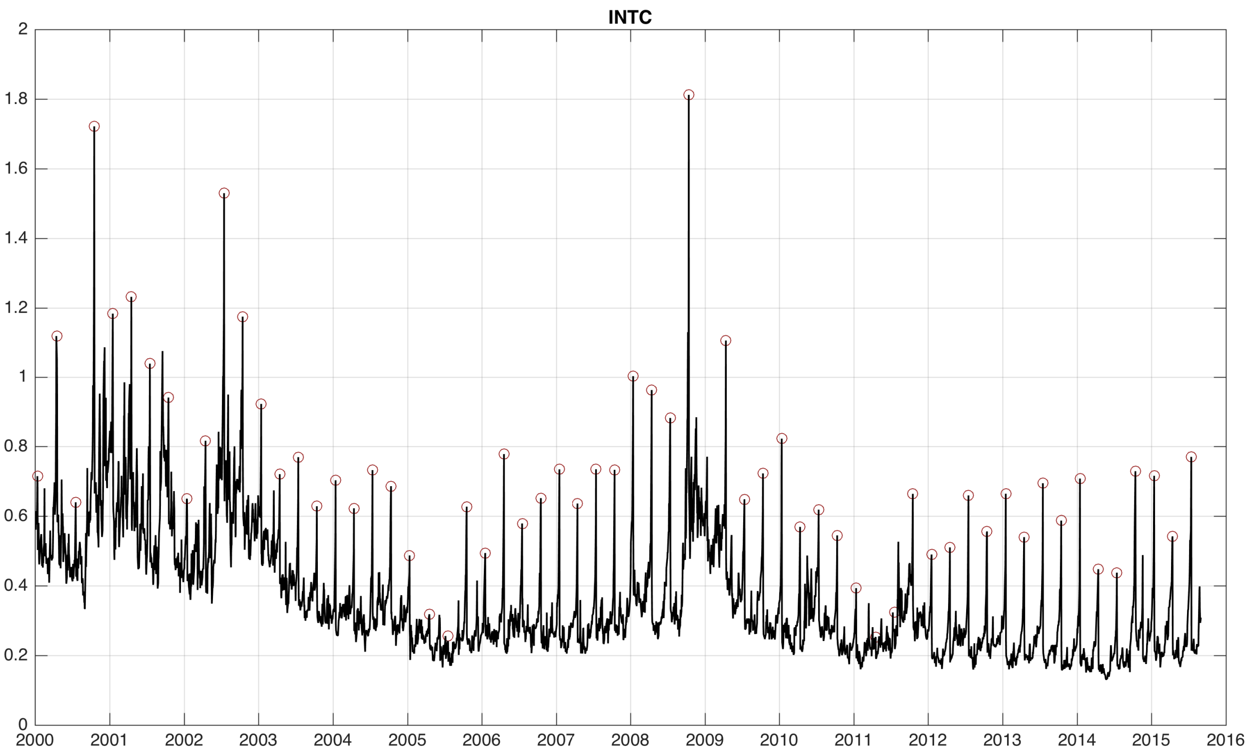
This paper studies the pricing of earnings risk in option prices.[1] These announcements generate fundamentally different risks compared to Brownian or Poisson risks in asset pricing models due to their predictable timing. To see this, Figure 1 graphs short dated option implied volatilities (IVs) for Intel Corporation with earnings announcement dates (EADs) marked with a circle. IVs increase predictably prior to and sharply decrease after earnings are announced (previously noted by Patell and Wolfson (PW) (1979, 1981)). The goal of this paper is to incorporate earnings announcements and risks into option pricing models, to use option prices to extract option-implied ex-ante information about the impact of earnings risks on equity prices, and to study the information content of these announcements.

On the theoretical side, we specify new option pricing models building on Piazzesi (2000) with deterministically timed jumps on earnings dates with random sizes. This "earnings risk" model naturally generates the IV patterns seen in the data and motivates estimators of the ex-ante equity price uncertainty associated with an earnings announcement, essentially

[1] This paper subsumes and extends Dubinsky and Johannes (2006).

Figure 1: **Short-term ATM implied volatility (Intel Corporation)**

This figure shows the implied volatility of Intel (INTC) calculated as the average of the put and call implied volatility of the contracts closest to at-the-money (moneyness is defined as K/F where F is the forward price of the underlying) for the shortest available option maturity. The sample period is from January 2000 to August 2015. Red circles indicate earnings announcement days.



the option implied price volatility associated with the news. A simplified version of our general model provides the intuition.

Consider an extension of the Black-Scholes model with a single, predictably timed price jump occurring at time τ_j (the EAD) whose size is normally distributed with a volatility of $\sigma_j^{\mathbb{Q}}$, where $\mathbb{Q}$ is the risk-neutral probability. Equity prices are log-normally distributed, and option prices are given by a modification of the Black-Scholes formula. For an option with time to maturity T and $t < \tau_j \leq t + T$, the IV at time t is

$$\sigma_{t,T} = \sqrt{\sigma^2 + \left(\sigma_j^{\mathbb{Q}}\right)^2 / T}, \tag{1}$$

where σ is the diffusive volatility. This simple model delivers three general implications of earnings announcements: (1) IVs increase continuously and nonlinearly prior to an EAD (as T decreases), (2) IV discontinuously falls after the announcement, and (3) the term structure of IV is downward sloping prior to the announcement. The first two of these implications generate the distinctive pattern in Figure 1 and were previously noted in Patell and Wolfson (1981). We will mainly rely on the third implication for our empirical work.

The central quantity is the ex-ante earnings price volatility $\sigma_j^{\mathbb{Q}}$, the risk-neutral anticipated announcement volatility. This parameter is a reduced form, capturing the impact of all information released, not just current quarter earnings or forward guidance. Earnings risks naturally vary over time and across firms, and an intermediate goal is to develop easy-to-compute and accurate option based estimators of this parameter.[2] Equation 1 can be used to develop ex-ante estimators of $\sigma_j^{\mathbb{Q}}$ using options of different maturities (term structure estimators) and ex-post estimators of $\sigma_j^{\mathbb{Q}}$ based on the post announcement decrease in IV (time series estimators).[3] We also consider more general models incorporating stochastic

[2]Estimating realized earnings announcement volatility is difficult using only a single observation.

[3]Although these estimators assume constant volatility, Section 2.2 shows the estimators are largely robust

volatility and Poisson driven jumps in prices and perform a structural estimation.

Given this theoretical framework, our main contributions are empirical. Using a broad dataset of actively traded firms from 2000 – 2015, we characterize the information embedded in options regarding earnings risks. We first extend the initial work of Patell and Wolfson (1981) testing the impact of earnings announcements on option prices. Two of our tests are related to those in PW, but the third is new. These tests document strong evidence that earnings announcements affect option prices (consistent with Figure 1).

Our next goal is to quantify earnings uncertainty. Using estimators derived from Equation 1, estimates indicate that ex-ante earnings uncertainty is large, statistically significant, and varies both across firms and time. There is a strong business cycle pattern, with the level and cross-sectional variation in earnings risks increasing substantially in recessions. For our sample, the average earnings uncertainty ranges from roughly $4\% - 6\%$ during pre and post crisis expansions to approximately $10 - 11\%$ at the height of the 2000 – 2002 or 2008 – 2009 recession, respectively. Cross-sectional earnings uncertainty dispersion increases in recessions, more than doubling from less than 3% to over 6%.

In terms of informational content, ex-ante option based estimates of earnings volatility are highly informative about future realized equity volatility: the ex-ante estimates have a correlation of more than 50% with subsequently realized price volatility after the announcement. This is close to what could maximally be expected given normal sampling errors in realized volatility. The cross-sectional correlation between option implied average earnings volatility and subsequent post-earnings daily equity volatility is roughly 85%. Earnings volatility estimates also provide incremental information in forecasting the following month's equity volatility relative to diffusive IV (e.g., Christensen and Prabhala (1998), Lamoureux and Lastrapes (1993), and Jiang *et al.* (2005)).

to stochastic volatility. We also calibrate formal stochastic volatility models in Section 4.7.

Another commonly used measure of firm level uncertainty is the dispersion in analysts earnings forecasts, based on the idea that firms with higher earnings uncertainty are more difficult to analyze, which in turn generates a broader range of analyst forecasts. We find no significant relationship between dispersion of analysts forecasts with our measure, consistent with Diether *et al.* (2002). We also find that in our sample the dispersion of analysts forecasts has no statistical ability to forecast post-earnings daily equity volatility.

We next analyze the pricing of earnings announcement risks. For index options, there is strong evidence for volatility and/or Poisson drive jump risk premiums (see, e.g., Pan (2002), Broadie *et al.* (2007)). Quantifying earnings volatility risk premiums is straightforward given precise estimates of $\sigma_j^{\mathbb{Q}}$ for each EAD, which can be compared to realized earnings volatility in a number of ways. One way compares averages of $\sigma_j^{\mathbb{Q}}$ to close-to-open equity return volatilities on EADs, which assumes all of the overnight price move is from earnings induced jumps. We also construct measures based on close-to-close returns, allowing for some 'digestion' time for prices to adjust after the open, compute standardized returns (which are less sensitive to outliers), and analyze straddle returns.

Every measure points to significant earnings jump risk premiums. Average option implied earnings day volatility is 8.22% for the full-sample compared to a realized announcement day volatility of 7.42%, a premium of 80 bps. Focusing only on close-to-open returns (assuming all of the effect occurs at the open), the average premium is 56 bps. Averages are sensitive to outliers, and the results are stronger using medians, trimmed estimates, or standardized returns. The risk premium is consistent with a significant systematic component in earnings risks: ex-ante earnings volatility estimates are strongly related to historical equity beta, with a correlation of roughly 60% across firms.

To connect earnings uncertainty risk premium estimates with economically interesting quantities, we compute at-the-money straddle returns on EADs. The straddle positions are opened prior to the EAD and closed the next day. The average (median) EAD straddle return is -8% (-10%). We compute bootstrap returns to account for the fact that straddle returns are generally negative, and results confirm statistically significant straddle returns consistent with an economically significant earnings jump risk premium. These risk premium results are related to robust patterns of equity returns around earnings dates. First noted by Beaver (1968), there are positive average equity returns for firms announcing earnings (see also Cohen *et al.* (2007) and Frazzini and Lamont (2007)). Savor and Wilson (2016) provide a model based explanation for the firm level earnings announcement premium. Our results contribute to this literature by documenting a robust earnings jump volatility risk premium.

Finally, we build continuous-time stochastic volatility (SV) models incorporating randomly timed and earnings induced price jumps. These models allow us to quantify the impact of earnings via option pricing errors and the relative importance of EADs, SV and randomly timed jumps. Using IVs, we estimate the SV models for some of the largest firms in our sample: Amazon, General Electric, IBM, Intel, Microsoft, and Qualcomm. We again find strong earnings effects, which are strongest around EADs where pricing errors can be more than 50% lower when incorporating earnings jumps. Pure SV models cannot fit term structure IV patterns observed around EADs, resulting in large pricing errors. For example, average pricing errors for AMZN the day prior to earnings are 8.11%, 2.53%, and 3.82% for short, medium, and long term options, respectively, and fall to 3.69%, 1.49%, and 1.70%, respectively, when incorporating earnings announcements. Although there are only four EADs per year, overall option pricing errors fall on average by almost 20%. EADs are far more important than Poisson price jumps.

Our results have other research implications. There is a growing literature using firm IVs, either directly or via a variance risk premium calculation, as regressors or for portfolio sorts. These procedures may be sensitive to EADs and factors such as option maturity that are unrelated to the research questions. For example, consider a firm with $\sigma = 25\%$ and an average sized earnings jump volatility of 7.3%. From equation 1, the IV of a 2 week option is almost 44% but only 32% for an option expiring in 6 weeks. Thus, for options spanning EADs, there is significant IV variation unrelated to fundamentals from maturity effects. An *et al.* (2014), for instance, sort stocks by changes in 30-day IVs, arguing that sharp increases in IV can be linked to informed trading. Our model suggests that firms with rapidly increasing IVs are also more likely to announce earnings. Similarly, Baltussen *et al.* (2016) use short-term options and calculate the standard deviation of the IV over a calendar month. Our model suggests that firms with the highest volatility of IV are biased towards announcing firms, given the pattern of IVs around EADs, independent of fundamentals. We show empirically that earnings announcements increase the noise in the measurement of IV-based sort variables and provide guidance on how to minimize the impact of earnings announcement related time variation in IVs on cross-sectional studies.

All of our implications generally apply to other predictable events including macroeconomic announcements and elections, referendums, summits or other scheduled meetings (e.g., OPEC semi-annual meetings). As an example, consider the Brexit vote on June 23rd, 2016. Just prior to the vote, 1-month and 2-month USD/GBP currency IV was 28.21% and 21.51%, respectively. The term structure estimate of the Brexit impact on the USD/GBP exchange rate was 7.45%. The pound fell 7.6% on the day following the vote. A similar pattern occurred prior to the US 2016 election. Kelly *et al.* (2016) analyze the impact of predictable national elections and global summits on option prices.

2 Incorporating Earnings Announcements in Equity Price Models

2.1 Stochastic Volatility Models

This section incorporates earnings announcement risks into continuous-time SV models. The first step is a model of how earnings announcements impact equity prices. Earnings announcements normally occur outside of normal trading hours, either after the 4:00 p.m. market close or before the formal 9:30 a.m. open. We assume earnings induce a jump or discontinuity in the continuous-time price path. The jump assumption is intuitive, consistent with existing work analyzing macroeconomic announcement effects (e.g., Piazzesi (2005) and Beber and Brandt (2006)), consistent with statistical evidence identifying announcements as the cause of jumps in jump-diffusion models (Johannes (2004) and Barndorff-Nielsen and Shephard (2006)), and parsimonious.[4] For earnings announced during normal market hours, Patell and Wolfson (1984) find the bulk of the price response occurs within the first few minutes. For earnings announced outside of normal market hours, Martineau (2017) argues earnings news arrives as a "jump", with 80% of the price response occurring within the first few trades after news is released (see also Lee (2012)).

Formally, N_t^d counts EADs prior to time t: $N_t^d = \sum_j \mathbb{1}_{[\tau_j \leq t]}$ where $\mathbb{1}$ is the indicator function and τ_j is an increasing sequence of predictable stopping times representing earnings announcements. The jump size, $Z_j = \log\left(S_{\tau_j}/S_{\tau_j-}\right)$, is distributed according to a known distribution, $Z_j|\mathcal{F}_{\tau_j-} \sim \pi\left(Z_j, \tau_j-\right)$. In addition to earnings jumps, price jumps can arrive at random times $\bar{\tau}_j$ via a Poisson process $\bar{N}_t$ with intensity $\bar{\lambda}_y$ and jump size $\bar{Z}_j$. We do

[4] Over finite sampling periods, it is always possible to construct a stochastic volatility model with similar distribution implications to a jump model. These models are generally more complicated than simple jump models, which is one reason why the literature typically models these events as price "jumps", rather than a large spike in diffusive volatility.

not consider other predictable events such as mid-quarter earnings updates, stock splits, or mergers and acquisitions although these do have interesting implications (see, e.g., Bester *et al.* (2013)). We assume a square-root SV process, thus prices and variance processes solve:

$$dS_t = \left(\mu - \bar{\lambda}_y \psi_t\right) S_t dt + \sqrt{V_t} S_t dW_t^s + d\left(\sum\nolimits_{j=1}^{N_t^d} S_{\tau_j -}\left[e^{Z_j} - 1\right]\right) + d\left(\sum\nolimits_{j=1}^{\bar{N}_t} S_{\bar{\tau}_j -}\left[e^{\bar{Z}_j} - 1\right]\right),$$
$$dV_t = \kappa_v\left(\theta_v - V_t\right) dt + \sigma_v \sqrt{V_t} dW_t^v,$$

where ψ_t is the random jump compensator and $dW_t^s dW_t^v = \rho dt$. This process is well defined in continuous-time.[5]

The jump Z_j captures the equity price response to the information released in the earnings announcement. Firms report the current quarter's cash flow, balance sheet and income statement, and many firms also provide forward-looking information and answer questions via conference calls with analysts and investors. The jump sizes translate this valuation-relevant information into shocks in equity prices. Therefore, the jump distribution π serves as a reduced form model of how fundamental information affects prices.

The volatility of Z_j, $\sigma_j^{\mathbb{P}} = std^{\mathbb{P}}\left(Z_j | \mathcal{F}_{\tau_j -}\right)$ is a central parameter of interest, capturing the ex-ante anticipated uncertainty regarding the equity price response to the announcement information. To understand its sources, consider an earnings response model of Ball and Brown (1968): $Z_j = \alpha + \beta\left(E_{\tau_j} - \hat{E}_{\tau_{j-}}\right) + \varepsilon_{\tau_j}$, where $\hat{E}$ is an estimate of current earnings. In this model, the equity price response is driven by unexpected earnings and other announcement shocks. The variance of equity prices due to the information released in the earnings announcement is $\left(\sigma_j^{\mathbb{P}}\right)^2 = \beta^2 var\left(E_{\tau_j} - \hat{E}_{\tau_{j-}} | \mathcal{F}_{\tau_j -}\right) + \sigma_\varepsilon^2$.

This useful decomposition implies that the earnings response coefficient β, the variance

[5]This process is a well-defined semi-martingale that is continuous from the right with left limits, see, e.g., Protter (2005) for formal definitions. Prices are a product of an affine component and a discrete jump at earnings announcements.

of unexpected earnings news, and other shocks drive the equity price response to earnings announcements. Empirically identifying the different sources of earnings induced equity volatility is difficult: earnings response models generate small R^2's, normally less than 10%, for various reasons (nonlinearities, inaccurate estimates of expected earnings, the importance of forward guidance, small samples, etc.). Imhoff and Lobo (1992) and Ang and Zhang (2005) report R^2's between 3-6%, which implies that most of the price response to earnings announcements is unexplained by standard regressors. This motivates our focus on the EAD jump volatility as a reduced form of the valuation relevant uncertainty.

To price options, we construct a measure $\mathbb{Q}$ under which discounted prices are martingales. Risk corrections for randomly timed jumps and Brownian motions are standard. At predictable EADs, the martingale restriction implies that the pre-jump expected value of the post-jump equity price equals the pre-jump equity price, that is $E^{\mathbb{Q}}\left[S_{\tau_j}|\mathcal{F}_{\tau_j-}\right] = S_{\tau_j-}$ (see Piazzesi (2000)). In terms of risk premiums, we assume that under $\mathbb{Q}$, prices and volatilities are affine, that the risk-neutral jump intensity is $\bar{\lambda}_y^{\mathbb{Q}}$ and $\bar{Z}_j(\mathbb{Q}) \sim \mathcal{N}\left(\bar{\mu}_y^{\mathbb{Q}}, \left(\bar{\sigma}_y^{\mathbb{Q}}\right)^2\right)$:

$$
\begin{aligned}
dS_t &= \left(r_t - \bar{\lambda}_y^{\mathbb{Q}} E_t^{\mathbb{Q}}\left[e^{\bar{Z}_j(\mathbb{Q})} - 1\right]\right) S_t dt + \sqrt{V_t} S_t dW_t^s(\mathbb{Q}) + d\left(\sum\nolimits_{j=1}^{N_t^d} S_{\tau_j-}\left[e^{Z_j(\mathbb{Q})} - 1\right]\right) \\
&\quad + d\left(\sum\nolimits_{j=1}^{\bar{N}_t(\mathbb{Q})} S_{\bar{\tau}_j-}\left[e^{\bar{Z}_j(\mathbb{Q})} - 1\right]\right) \\
dV_t &= \kappa_v^{\mathbb{Q}}\left(\theta_v^{\mathbb{Q}} - V_t\right) dt + \sigma_v \sqrt{V_t} dW_t^v(\mathbb{Q}).
\end{aligned}
$$

The only no-arbitrage constraint for jump distribution measure changes is common support, thus, for example, state variables could appear in one measure but not the other or that the distributional form could change. We assume EAD jump sizes are normal under $\mathbb{Q}: \pi^{\mathbb{Q}}\left(Z_j|\mathcal{F}_{\tau_{j-}}\right) \sim \mathcal{N}\left(-\frac{1}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2, \left(\sigma_j^{\mathbb{Q}}\right)^2\right)$. This is parsimonious: there is a single earnings jump parameter on each EAD and estimating $\sigma_j^{\mathbb{Q}}$ is a primary focus of the paper. The model is affine, facilitating option pricing. Appendix A.1 discusses option pricing in the general

SV model. We use this model for formal structural estimation. The next sections use a simplified version to develop easy-to-implement and robust estimators of $\sigma_j^{\mathbb{Q}}$.

It is useful to note that deterministic and random price jumps have fundamentally different effects on the shape and dynamics of IV curves, and hence these different model classes are identified by entirely different data. The steepness of the short term IV curve is particularly informative about the parameters of the random jump process (see for instance Broadie *et al.* (2007)) whereas deterministic jumps have virtually no effect on the slope of IV curves, see Equation (1). In contrast, deterministic jumps affect the term structure and the time-series behavior of IVs, two features that are largely unaffected by Poisson driven price jumps. Our estimation procedure captures these model features and allows us to extract earnings announcement jump information from ATM options only. Out-of-the-money (OTM) and in-the-money (ITM) options are useful in our framework mainly to distinguish between random jumps, SV and earnings announcement jumps.

2.2 A Simple Model and Earnings Uncertainty Estimators

To estimate $\sigma_j^{\mathbb{Q}}$, consider a model with constant volatility and price jumps on EADs:

$$S_t = S_0 \exp\left[\left(r - \frac{1}{2}\sigma^2\right)t + \sigma W_t\left(\mathbb{Q}\right) + \sum\nolimits_{j=1}^{N_t^d} Z_j\left(\mathbb{Q}\right)\right], \tag{2}$$

where $Z_j\left(\mathbb{Q}\right) = -\frac{1}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2 + \sigma_j^{\mathbb{Q}}\,\varepsilon_j(\mathbb{Q})$ and $\varepsilon_j(\mathbb{Q}) \overset{i.i.d}{\sim} N(0,1)$. Since $W_t\left(\mathbb{Q}\right)$ and $\sum_{j=1}^{N_t^d} Z_j\left(\mathbb{Q}\right)$ are normally distributed, prices are log-normal. A European option with time to maturity T is given by the Black-Scholes formula with a modified volatility input:

$$\sigma_{t,T}^2 = \sigma^2 + T^{-1} \sum_{j:\ t<\tau_j\leq t+T} \left(\sigma_j^{\mathbb{Q}}\right)^2. \tag{3}$$

This model provides the main implications of earnings announcements for option prices. First, assuming one announcement before maturity, annualized implied variance is $\sigma^2_{\tau_j-,T} = \sigma^2 + T^{-1}\left(\sigma_j^{\mathbb{Q}}\right)^2$ just before the announcement and $\sigma^2_{\tau_j,T} = \sigma^2$ after the announcement. Thus, IV discontinuously drops immediately after the announcement. Second, implied variance increases at the rate proportional to T^{-1} into the event. Third, holding the number of jumps constant, the term structure of IVs slopes downward.

This suggests two estimators of $\sigma_j^{\mathbb{Q}}$, one based on the IV term structure and the other based on IV dynamics. Given two options with time to maturity T_1 and T_2 ($T_1 < T_2$) and a single EAD prior to maturity, then $\sigma^2_{t,T_1} > \sigma^2_{t,T_2}$ and $\sigma_j^{\mathbb{Q}}$ can be estimated via:

$$\left(\sigma^{\mathbb{Q}}_{j,\,term}\right)^2 = \frac{\sigma^2_{t,T_1} - \sigma^2_{t,T_2}}{T_1^{-1} - T_2^{-1}}. \tag{4}$$

We label this ex-ante estimator the *term structure* estimator as it uses IV term structure information prior to the EAD. The second estimator uses changes in IV. Assuming an earnings announcement after the close on date t (or before the open on the next trading date), then the post-announcement IV is σ (assuming no other EADs prior to maturity). Solving for earnings jump volatility gives the *time series* estimator

$$\left(\sigma^{\mathbb{Q}}_{j,\,time}\right)^2 = T\left(\sigma^2_{\tau_j-,T} - \sigma^2_{\tau_j+1/252,T-1/252}\right). \tag{5}$$

To provide a concrete example, on October 23, 2014, Amazon.com released earnings after market close. The IV of at-the-money (ATM) options expiring in 8 and 15 days was 75.28% and 54.37%, respectively, which implies $\sigma^{\mathbb{Q}}_{j,\,term} = 10.26\%$. Short-dated option IV falls to 29.36% after the EAD, which implies $\sigma^{\mathbb{Q}}_{j,\,time} = 9.87\%$. This is a typical example with quantitatively similar estimates, even if they use different information.

Although these estimators assume no SV or randomly-timed price jumps, estimates are quite robust to both factors. To see this, consider parameter values in line with Bakshi *et al.* (2012) and our estimates in Section 4.7: $\theta_v^{\mathbb{Q}} = 0.4^2$, $\sigma_v = 0.6$, $\rho = -0.4$, $\bar{\lambda}_y^{\mathbb{Q}} = 5$, $\bar{\mu}_y^{\mathbb{Q}} = 0$, $\bar{\sigma}_y^{\mathbb{Q}} = 0.05$ and $\sigma_j^{\mathbb{Q}} = 0.08$. For the term structure estimator, the main bias arises from mean reversion in V_t when spot volatility is significantly higher or lower than its long run average. To understand the bias magnitude, consider an extreme case where $\kappa_v^{\mathbb{Q}} = 2$ (about twice the value we estimate in Section 4.7) and that V_t is twice its long-run average. For typical maturities in our sample, $T_1 = 2/52$ and $T_2 = 6/52$, $\sigma_{term}^{\mathbb{Q}} = 0.0848$. If spot variance is 50% of its long run value, $\sigma_{term}^{\mathbb{Q}} = 0.0785$. These biases of individual estimates of $\sigma_j^{\mathbb{Q}}$ are small in absolute terms, but also relative to microstructure noise. For example, typical bid-ask spreads on equity options are at least \$0.05 to \$0.10 for options that are often less than \$1 or \$2, which could induce significant noise in IVs. In addition, since the term structure in our sample is flat on average, any biases are likely to average out over the sample period.

Building on Merton (1976), Hull and White (1987), and Bates (1996), Appendix A.2 analyzes the estimators under model misspecification. The term structure estimator is robust for many reasons: (a) it does not depend on σ_v or realized shocks; (b) diffusive volatility is highly persistent, thus $\kappa_v^{\mathbb{Q}}$ is small; (c) the term structure of IV is flat, which implies that $\theta_v^{\mathbb{Q}} \approx \theta_v$ and/or that $\kappa_v^{\mathbb{Q}}$ is very small; and (d) we use short-dated options, typically less than two months. The time series estimator is less robust as it relies on shock realizations over the next day and is sensitive to any lagged responses. These biases could directionally bias the results: large positive shocks downward-bias estimates more than large negative shocks upward-bias estimates (see Appendix A.2). Although we report both, the time series estimator is noisier, thus we primarily focus on the term structure estimates.

2.3 Literature Review and Discussion

Our work relates to a number of papers using time series data to analyze earnings announcements. A large literature (e.g., Ball and Brown (1968), Kim and Verrecchia (1991), Penman (1984), etc.) analyze the equity price response to earnings announcements. There are also anomalous movements around EADs (e.g., Bernard and Thomas (1990), Frazzini and Pedersen (2014), Barber *et al.* (2013)). Hanweck (1994) finds that Treasury bond and Eurodollar futures are more volatile on unemployment announcement days and builds a model to capture this effect.[6] Patell and Wolfson (1984) study the price response to intraday earnings announcements using transaction data and find most of the response occurs within minutes, which is important as we assume announcements induce a discontinuous jump. Maheu and McCurdy (2004) analyze GARCH jump models, assume the jump intensity increases on EADs, and find that many of the jumps they identify occurred on EADs. Andersen *et al.* (2003), Bernanke and Kuttner (2005), Savor and Wilson (2013) and Lucca and Moench (2015) study the impact of predictable macroeconomic announcements on equity prices.

Our paper is closely related to Patell and Wolfson (PW) (1979, 1981) who provide early descriptive work on IV dynamics around EADs. Their model has deterministically changing diffusive volatility and test whether IV increases prior to and drops after an EAD. Patell and Wolfson (1979) find mixed evidence using annual EADs from 1974 to 1978, while Patell and Wolfson (1981) find stronger evidence using quarterly EADs from 1976 to 1977. There are a number of importance differences between our approach/results and PWs. First, we can easily incorporate SV in our model, while extending PW to handle SV requires deterministically-timed jumps in SV. Second, PW's model does not allow earnings uncertainty to change across measures, as it is a diffusive model. Third, we provide ex-ante

[6]We would like to thank Bob McDonald for pointing out Hanweck (1994), an unpublished Ph.D. dissertation.

estimators of anticipated earnings risks. Fourth, we do not require any assumptions about π. Fifth, PW do not directly estimate the earnings uncertainty, rather they test the increase and decrease in IV.

Ederington and Lee (1996) and Beber and Brandt (2006) analyze announcement effects in Treasury bond futures options. Ederington and Lee (1996) find that IV falls after announcements. Beber and Brandt (2006) analyze the implied pricing density and find that, in addition to IV falling, implied skewness and kurtosis also change. Related to this, Donders and Vorst (1996), Donders *et al.* (2000) and Isakov and Perignon (2001) apply PW's approach to European options markets. Whaley and Cheung (1982) argue that the informational content of earnings announcements is rapidly incorporated into option prices whereas Diavatopoulos *et al.* (2012) test whether option-implied skewness and kurtosis provide information about subsequent equity and option returns around EADs.

Kelly *et al.* (2016) study the pricing of political risk around events such as elections, and document strong effects generated by their predictable timing, consistent with our results from earnings announcements. Their model differs from ours as elections may induce a policy shift, which in turn, could persistently shift volatilities. Pástor and Veronesi (2013) provide additional equilibrium results.

Subsequent to Dubinsky and Johannes (2006), Barth and So (2014) use our estimators to study the impact of earnings announcements on market-wide, non-diversifiable volatility risk. They find earnings announcements contribute to volatility changes and command a premium. Rogers *et al.* (2009) study how management earnings forecasts affect IV, arguing that bad news disclosure affects short- and long-term IV whereas long-term IV remains unaffected by other disclosures. Neururer *et al.* (2015) find that the uncertainty measured by IVs prior to EADs declines with the firms' reputation. Billings and Jennings (2011) normalize option prices prior to announcements by the standard deviation of analysts' earnings forecast to separate equity market reaction to earnings information from earnings uncertainty.

3 Data

We use option price data from OptionMetrics' IvyDB. Due to microstructure concerns such as bid-ask spreads and non-synchronous trading, we focus on actively traded firms. For each calendar year in our sample, we rank all firms by dollar trade volume. From each of these yearly rankings, we eliminate firms with an average quarterly dividend yield of more than 2% and firms whose equity price traded below \$5. The focus on firms without excessive dividend yields minimizes any issues associated with pricing options on high-dividend firms. Unlike indices, whose dividend payments are usually modeled as continuous, dividends on individual equities are discrete. Options on low equity price firms generates numerical issues when computing IVs because strikes are usually quoted in either \$1 or \$2.5 increments, implying that options are often either extremely deep in-the-money or out-of-the-money. Finally, we limit our analysis to firms with CRSP share code 10 or 11 (common stock).

Next, we identify the exact date and time of the earnings announcements from Thomson Reuters, the Institutional Brokers Estimate System (IBES) and Compustat. Thomson Reuters and IBES provide dates and times (either a time stamp or an indicator to determine if the announcement was before market open or after market close), whereas Compustat only provides dates. We find substantial disagreement over the dates and/or exact times (see also DellaVigna and Pollet (2009)) and use the following reconciliation approach. First, we require that the EAD is recorded in at least two of the three sources. As we focus on actively traded firms, there are only occasional gaps in Thomson Reuters' coverage while Computstat and IBES provide nearly full coverage. If there is date or time disagreement, we search the *PR Newswire*, *Business Wire* and *Wall Street Horizon* in LexisNexis to identify the correct date and/or time. If the LexisNexis search is unsuccessful, either because there are no news items or we cannot identify the timing, we record the announcement as missing.

Our sample is restricted by OptionMetrics data availability (1/1996 until 8/2015) and Thomson Reuters (first full calendar year is 2000). IBES and Compustat provide longer data histories. Since the exact announcement time is crucial for our analysis (and because of issues with IBES), we restrict the sample from 1/2000- 8/2015.[7] After applying the filters, we select the 50 most liquid firms each year. Our liquidity-driven sample selection is similar to Carr and Wu (2009) and Bakshi *et al.* (2012), although we apply our criteria year by year rather than to the full sample, avoiding potential biases due to delistings (such as Dell), default (such as Lehman), merger activity (such as Chase Manhattan and J.P. Morgan) or IPOs (such as Google). A range of highly liquid firms remain in the sample throughout the entire 16 year period: Amazon (ticker: AMZN), General Electric (GE), Intel (INTC), International Business Machines (IBM), Microsoft (MSFT) and Qualcomm (QCOM). On the other hand, many of the overall 196 firms pass the selection criteria in few years.

We obtain option information for all available contracts. IVs are based on best bid and offer price midpoints and are adjusted for dividends and early exercise. We eliminate strike/maturity combinations with zero volume, zero IV, or maturities more than one year. We next eliminate options with less than three days to maturity, as microstructure issues are magnified with extremely short-dated options. For every day and expiration date, options are sorted by moneyness, and we record IVs for the nearest to-the-money strike. We define moneyness as $M \equiv K/F_{t,T}$ where K is the strike and $F_{t,T}$ the time t forward price with time to maturity T.[8] ATM options are most actively traded and provide the cleanest information on expected volatility. For each strike/maturity, call and put IVs need not be identical, due

[7]Removing the first four years from our sample has no effect on our results. An earlier version of this paper included options from this sub-period and found qualitatively and quantitatively similar results.

[8]We calculate forward prices using the dividend information in OptionMetrics as well as the zero curve file which provides risk-free rates.

to the American feature, microstructure noise such as bid-ask spreads or stale quotes. Since OptionMetrics reports close prices, stale quotes are a concern. Battalio and Schultz (2006) argue that stale option quotes bias put-call parity tests. To minimize this, we average call and put IVs for the closest to-the-money strike for a given maturity.[9] If call and put IV differences are extreme, we eliminate the option pair from our dataset.

Table 1 (Panel A) shows that there is increased trading around earnings announcements. The average daily dollar volume is about twice as high on the first trading day after earnings announcement compared to ordinary trading days within a 40 day window around the announcements. These patterns are robust across sub-samples, although the overall trading in equity options has increased markedly over time. Panel B shows that there is a slightly higher bid-ask spread on the day after earnings announcements, but the economic differences are rather small. For instance, pooled average bid-ask spreads for ATM options are 6.17% on EADs versus 6.05% over the period from 11 to 20 trading days after the announcement. Note that quoted bid-ask spreads are a very rough measure of trading cost, Muravyev and Pearson (2016) show that real trading costs in option markets may be substantially lower.

[9]To see how this mitigates the stale quote problem, consider an example. Consider an ATM call and put option with $T-t = 1/12$, $S_t = \$20$, $\sigma = 20\%$ and $r_t = 5\%$). The call and put prices are \$0.5024 and \$0.4193. If we assume that option quotes do not change (they are priced assuming the equity price is \$20) and that the closing equity price is actually \$20.10, the IVs are not 20%, but 22.28 for the call and 17.918 for the put, generating problems put-call parity tests, such as those in Battalio and Schultz (2006). Our averaging procedure generates an IV of 20.09 percent, close to the true IV. In practice, averaging also reduces problems with bid-ask spreads. Pan and Poteshman (2006) use a similar procedure. Another possibility would be to employ intradaily option data in our analysis which is now available for part of our sample period from various data vendors. Due to the extreme computational burden of intra-daily option data (see Muravyev *et al.* (2013)) and the benchmark character of OptionMetrics in the related literature, we focus on daily closing prices.

Table 1: **Average Dollar Volume and Bid-Ask Spreads around Earnings Announcements.**

Panel A provides the average daily dollar trading volume (mid dollar price of option contract times traded volume) averaged over all firms in our sample and over trading days prior and after earnings announcements. Column 2 (-20 to -10) provides the average trading volume 20 to 10 trading days before the announcements. Column 5 (0) is the volume on the day prior to the announcement, column 6 (1) is the volume on the first day after the announcement (i.e. the day after the announcement for an AMC announcement and the same day for a BMO announcement). Other columns follow identical patterns. Panel B provides average bid-ask spreads for option with strikes between 95% and 105% of the current stock price (we divide by the mid dollar price of the option).

Days re-altive to EA	-20 to -10	-9 to -5	-4 to -1	0	1	2 to 5	6 to 10	11 to 20
Panel A: Average Dollar Volume (in 100 Million USD)								
2000 - 2005	10.26	9.66	10.74	12.99	17.84	9.92	8.42	9.76
2006 - 2010	19.84	23.82	20.36	36.41	42.92	22.42	21.82	20.34
2011 - 2015	22.56	29.96	27.70	46.66	65.79	26.84	36.05	32.38
Pooled	17.07	20.37	18.99	30.74	40.48	19.07	21.14	20.04
Panel B: Average Bid-Ask Spread for ATM options (in Percentage of the Mid Option Price)								
2000 - 2005	5.27	5.50	5.50	4.86	5.64	5.36	5.32	5.79
2006 - 2010	4.82	4.99	4.92	5.04	5.26	4.83	4.84	5.11
2011 - 2015	7.11	6.65	6.02	6.28	7.71	7.00	7.16	7.30
Pooled	5.70	5.70	5.47	5.37	6.17	5.70	5.75	6.05

4 Empirical Evidence

4.1 Summary Statistics

Table 2 provides equity return statistics for firms with at least 7 years of EADs pooled by year. EAD return volatility is substantially higher than non-EAD volatility as variance ratios are close to six on average. The effect varies across firms and the business cycle, indicating strong heterogeneity in the pricing of earnings news. For example, our results imply that in 2015 more than 19% of the total annualized variance of individual equity returns occurred on EADs.[10] EAD volatilities are significantly higher during the 2000-2001 recession and in 2008. In 2008, due to the higher level of diffusive volatility, a similar calculation shows that total EAD variance drops to 6.2% of total variance, consistent with a greater role for non-firm specific systematic macroeconomic volatility. If volatility was constant across days, EADs would generate $4/252 \approx 1.6\%$ of the total annualized variance. Earnings announcements generate a large, disproportionate share of overall volatility, with a time-varying impact.

Table 3 disaggregates the data at the firm level. Note first that the number of EADs varies as firms enter and exit the sample based on trading volumes. There is a wide range of firms in terms of the relative importance of EADs. For example, NFLX has a variance ratio of 47.32, indicative of a relatively large amount of information on EADs. Presumably for firms like NFLX, it is difficult to obtain valuation relevant information like subscribers or revenue from public sources. For other firms, such as COP, CVX, FCX, or XOM, earnings announcements provide little information as these firms' earnings are driven by publicly available information like commodity prices. Altria's (the former Phillip Morris) earnings announcements have little impact – not surprising given that this firm was involved in decades

[10] For example, in 2015, dividing the variance on EADs, 4×7.41^2, by the total non EAD variance, $4 \times 7.41^2 + 248 \times 1.93^2$ is 19.37%.

Table 2: **Summary statistics for the underlying returns (pooled)**

This table provides summary statistics for daily percentage equity returns for all firms in our sample from January 2000 until August 2015, pooled by calendar year. Summary statistics are provided for earnings announcement dates and trading days without earnings announcements. We report volatility (Vol), skewness (Skew) and kurtosis (Kurt) as well as the ratio (Var Ratio) between EAD and non EAD variance. The last column provides the number of EADs in our sample.

Ticker	EAD Vol	NonEAD Vol	Var Ratio	EAD Skew	Non EAD Skew	EAD Kurt	Non EAD Kurt	Num EAD
2000	9.60	5.80	2.74	0.47	0.53	3.10	7.49	190
2001	9.63	5.37	3.22	0.01	0.50	4.34	7.66	193
2002	7.13	3.38	4.44	0.23	-0.25	5.90	11.58	192
2003	5.43	2.13	6.46	0.67	1.03	5.15	21.53	196
2004	7.24	2.49	8.45	-0.87	16.08	10.66	833.01	192
2005	5.18	1.91	7.34	0.37	-0.39	6.66	41.93	199
2006	6.21	1.80	11.89	-0.61	0.48	5.27	10.16	197
2007	7.13	2.19	10.57	1.24	0.48	12.42	12.44	192
2008	9.38	4.62	4.12	-0.14	0.85	6.91	19.47	197
2009	7.23	3.01	5.75	0.92	0.63	6.20	12.76	193
2010	5.41	1.88	8.33	0.90	0.44	7.15	10.63	200
2011	6.82	2.28	8.90	-1.45	0.25	10.95	18.55	200
2012	7.65	1.80	18.13	-0.75	0.41	12.53	13.15	200
2013	7.70	1.76	19.15	1.32	1.57	8.35	45.64	199
2014	5.98	1.75	11.70	0.36	-0.01	6.28	12.18	197
2015	7.41	1.93	14.76	-0.45	0.45	5.42	19.53	150
Pooled	7.32	3.06	5.71	0.15	1.18	7.83	44.03	3087

long tobacco litigation and the firm provides frequent corporate updates on non-EADs, thus earnings announcements have little content. Overall, there is substantial cross-sectional and times series variation in the impact of valuation relevant information released on EADs.

The model in Equation 2 assumes *conditionally* normally distributed returns, but since volatility changes across EADs, returns are not *unconditionally* normal, consistent with the data. Non-EADs generally have greater non-normality than EADs, consistent with SV and non-EAD price jumps. If random jumps are present, the low skewness indicates near zero jump means, thus Merton (1976) implies that these types of jumps will not adversely impact

Table 3: **Summary statistics for the underlying returns (by firm)**

This table provides summary statistics for daily percentage equity returns for all firms with at least seven years of EAD data from January 2000 until August 2015. Summary statistics are provided for earnings announcement dates and for trading days without earnings announcements. We report volatility (Vol), skewness (Skew) and kurtosis (Kurt) as well as the ratio (Var Ratio) between EAD and non EAD variance. The last column provides the number of EADs in our sample.

Ticker	EAD Vol	NonEAD Vol	Var Ratio	EAD Skew	Non EAD Skew	EAD Kurt	Non EAD Kurt	Num EAD
AAPL	6.12	2.55	5.77	-0.27	-2.65	2.31	60.55	51
AIG	3.73	1.93	3.73	-0.86	0.61	3.26	12.22	36
AMGN	5.59	2.34	5.74	0.44	0.41	3.70	7.23	40
AMZN	12.41	3.28	14.34	0.26	1.18	2.37	16.24	63
BA	3.67	1.99	3.41	-0.19	0.30	2.34	8.05	27
BAC	4.93	2.30	4.58	-2.61	0.91	15.50	27.15	51
C	3.26	1.81	3.24	0.74	-0.08	6.32	8.07	47
CAT	4.96	1.96	6.40	-0.42	0.24	3.06	8.49	46
COP	2.69	2.17	1.53	-1.05	-0.13	5.34	9.30	28
CSCO	7.71	2.51	9.42	0.62	0.54	3.78	10.98	60
CVX	1.74	1.74	1.00	-0.47	0.57	2.90	19.39	36
DELL	6.87	2.68	6.58	-0.14	0.46	3.26	7.75	28
EBAY	7.96	3.53	5.09	-0.06	0.77	3.54	12.02	30
FCX	4.10	3.22	1.63	-0.31	0.13	3.42	10.51	43
FSLR	16.41	4.24	14.95	0.52	0.79	1.89	13.91	27
GE	4.06	1.94	4.39	-0.10	0.45	5.30	12.09	63
GOOGL	7.19	1.77	16.52	0.41	0.14	2.67	8.56	43
GS	4.02	2.19	3.37	2.11	0.81	8.51	21.13	55
IBM	5.22	1.58	10.90	0.19	0.19	3.76	8.11	63
INTC	5.97	2.38	6.29	0.13	-0.13	5.08	9.06	62
JNJ	1.74	1.18	2.18	0.15	-0.93	1.99	19.97	36
JPM	3.60	2.62	1.89	0.97	0.88	4.74	18.53	59
MA	7.13	2.29	9.72	0.59	0.27	2.81	10.47	27
MO	1.77	1.63	1.17	0.05	0.28	2.87	14.63	44
MRK	3.17	1.65	3.70	-0.12	-1.67	2.74	37.20	40
MS	5.97	3.74	2.54	-2.05	6.38	9.43	158.41	31
MSFT	5.99	1.88	10.15	0.23	0.28	4.21	10.29	62
NEM	3.69	2.11	3.07	0.26	0.08	2.87	4.59	28
NFLX	20.91	3.04	47.32	-0.15	0.37	2.17	6.54	27
PFE	3.38	1.49	5.11	-1.04	-0.01	4.73	7.33	47
PG	3.12	1.38	5.14	-0.60	-3.64	2.90	93.59	52
QCOM	6.19	2.72	5.17	-0.23	0.30	3.43	8.82	63
SHLD	8.96	3.03	8.72	0.36	1.12	2.62	11.13	27
T	2.42	1.43	2.86	-0.40	0.98	3.96	17.54	35
UPS	2.57	1.26	4.14	0.43	0.20	2.89	8.40	28
VZ	2.58	1.46	3.10	1.29	-0.09	5.30	8.08	36
WFC	8.63	3.21	7.22	2.85	1.06	10.69	19.65	31
WMT	2.65	1.35	3.84	0.29	0.34	2.39	8.36	51
X	5.14	3.82	1.81	0.25	-0.09	2.26	6.44	27
XOM	2.21	1.57	1.98	-1.10	0.42	4.76	16.79	51
YHOO	8.90	3.28	7.34	-0.11	1.13	2.86	23.20	47

our estimators that use ATM options.

To economize on space, Appendix A.3 reports tests of the assumption that earnings announcements induce a jump or discontinuity in economic trading time. The volatility of close-to-open returns on EADs is more than three times higher than on non-EAD days, indicating that EADs are outliers or “abnormally” large movements. The volatility of open-to-close returns is only slightly higher for EADs, consistent with the presence of jumps induced by earnings announcements, full digestion by market open as in (see Martineau (2017)), and inconsistent with a continuous sample path (as in Patell and Wolfson (1979) and Patell and Wolfson (1981)).

4.2 Nonparametric Tests

This section tests the three main implications of earnings announcements on option prices: (1) IV increases prior to an EAD; (2) the term structure of IV is downward sloping before the EAD; and (3) IV decreases after the announcement.

The first tests use the Fisher sign and the Wilcoxon signed rank nonparametric tests to evaluate if a data series is positive or negative. Under the null that EADs have no impact, the Wilcoxon signed-rank test assumes the distribution is symmetric around zero, while the Fisher test assumes a zero median. For both, for example, the shape (normal versus t-distribution) and variance could change over time. We use one-sided tests to examine IV increases or decreases. PW (1979, 1981) use the same tests, although our implementation differs because we use changes in variance (as opposed to volatility), as this is the main model implication.[11] The time series tests compare IV changes for the shortest maturity options with at least three days to maturity post announcement. To test the IV increase

[11] The Fisher test gives the same result using either volatilities or variances, as it only depends on signs and is invariant to monotonic transformations.

pre-announcement, we subtract the ATM IV one trading day before the announcement from the ATM IV two weeks prior to the announcement.[12] Our results are not sensitive to these choices and are similar if we use the IV change over one week or increase the minimum time-to-maturity constraint. For the decrease in IV, we use the one day change around the EAD. If data are missing for the shortest maturity, we move one day in either direction. For the term structure tests, we use ATM options for the first two available maturities.

To economize on space, we summarize the findings and report detailed results in Tables A.3 and A.4 in Appendix A.4. The term structure and post EAD decrease implications holds for all years, while the increase in IV prior to EADs holds for every year except for 2009 when the Fisher test is insignificant. 2009 marked the end of the crisis, market and firm volatilities fell dramatically, and volatility of volatility was quite high.[13] At the firm level, the null of no post EAD decrease is rejected for every firm. These rejections provide strong evidence given our modest sample sizes (between 27 and 63 earnings dates per firm), supporting our reduced-form model and the importance of EADs. The term-structure evidence is also strong at the firm level, with only one exception (Altria, ticker MO), which was discussed above. The fact that IVs sometimes fall in the two weeks prior to an EAD is not surprising, given that volatility of two week changes is large (further evidence is provided in Appendix A.5). For example, for many firms, a large decrease in market volatility leading into a firm's EAD would likely be sufficient to generate an overall decrease in IV. Despite the small sample size, even for this test we reject the null of no effect for the vast majority of firms. Not surprisingly, the firms with the weakest evidence also had the smallest increases in return volatility on EADs. Appendix A.6 discusses the impact of SV on these results.

[12] We are careful to ensure that both IVs are calculated from options with the same maturity date.

[13] The VIX index fell from approximately 50% to 20% by the of 2009.

4.3 Characterizing Anticipated Earnings Volatility

Tables 4 and 6 provide firm-level summaries of the term structure and time series estimates of $\sigma_j^{\mathbb{Q}}$ given in Equations (4) and (5). We average these estimators in volatility units which is conservative due to Jensen's inequality.[14] Earnings announcement volatilities are large and statistically significant. Across firms, the average term-structure estimate is 6.87% and for nearly all firms the mean is greater than the median, indicating positive skewness. These ex-ante earnings risks can be extremely high: for Amazon.com (AMZN), for instance, a historical three standard deviation confidence band for the EAD return is ±36%. Thus, very large moves around EADs are clearly priced in options. Our estimates can easily generate the spikes in Figure 1.[15] Earnings volatility estimates also vary substantially across firms. For example, earnings volatility for AMZN, FSLR and NFLX average over 10%, while other firms average less than 3%.

Table 4 also reports error dates. The column labeled Err_1 counts the number of EADs for which $\sigma_{t,T_1} < \sigma_{t,T_2}$. A small number of error dates are not surprising for the reasons already discussed. First, error dates are concentrated in firms with low earning announcement volatility. Many of the largest and most actively traded firms have no error dates at all, suggesting microstructure or liquidity issues as possible causes. Second, the magnitudes of errors are quite small. There are only two dates on which $\sigma_{t,T_2} - \sigma_{t,T_1} > 5\%$. As a comparison, option bid-ask spreads for the maturities we use are around 5%, in terms of IV. This is especially relevant for firms with low earnings volatility (such as BAC, C, CVX, JNJ, JPM, MO, MRK, or XOM), as the differences in IVs for options on these firms are

[14] Jensen's inequality implies that the average of the standard deviations is less than the square root of the average variances since $\left(N^{-1}\sum_{j=1}^{N}\sigma_j\right)^2 < N^{-1}\sum_{j=1}^{N}\sigma_j^2$.

[15] Consider the following example. Assume the annualized diffusive volatility is constant at 40%, which implies that daily diffusive volatility is about 2.5% ($0.40/\sqrt{252}$). If the anticipated earnings uncertainty is 10%, then the annualized IV of an ATM option expiring in one-week is about 92% prior to the announcement and then subsequently falls to 40%.

Table 4: **Anticipated uncertainty (term structure estimator, by firm)**

This table provides the average estimate of anticipated uncertainty $\sigma_j^{\mathbb{Q}}$ using the term-structure estimator $\sigma_{term}^{\mathbb{Q}}$. We report the summary statistics over the sample period from January 2000 until August 2015 for all firms with at least seven years of EAD data. We report the mean, (Mean), median (Median), the standard error (Std Error), and the lower and upper quartile (25% and 75%) of all observations without errors. Err_1 counts the number of EAD on which the hypothesis of a decreasing term structure is violated, Err_2 counts the number of EAD on which the violations were more than 5% (i.e. $\sigma_{t,T_2} - \sigma_{t,T_1} > 0.05$). The last column provides the number of observations (Obs).

Term	Mean	Median	Std Error	25%	75%	Err_1	Err_2	Obs
AAPL	8.83	8.49	0.40	7.08	9.76	0	0	51
AIG	5.21	5.07	0.52	3.03	5.98	4	0	36
AMGN	5.46	4.79	0.47	3.60	6.64	4	0	40
AMZN	12.06	11.06	0.49	9.49	13.94	0	0	63
BA	4.33	4.09	0.29	3.35	5.01	2	0	27
BAC	3.96	3.31	0.47	2.28	4.69	5	0	51
C	3.34	2.90	0.21	2.29	4.48	8	0	47
CAT	5.67	5.07	0.38	4.31	6.13	0	0	46
COP	3.33	2.89	0.49	1.72	4.11	4	0	28
CSCO	8.13	7.28	0.35	6.59	9.10	0	0	60
CVX	2.53	2.52	0.19	1.85	2.94	11	0	36
DELL	6.25	5.90	0.51	4.53	7.06	4	0	28
EBAY	8.36	8.48	0.57	6.74	10.20	0	0	30
FCX	5.26	4.95	0.40	3.36	6.38	4	0	43
FSLR	14.13	14.17	0.67	11.14	16.02	1	1	27
GE	4.17	3.48	0.37	2.75	4.10	4	0	63
GOOGL	7.94	7.60	0.45	6.22	9.33	0	0	43
GS	4.98	4.00	0.41	3.17	5.93	6	1	55
IBM	5.68	5.02	0.30	4.49	6.15	0	0	63
INTC	7.04	6.27	0.36	5.31	7.66	1	0	62
JNJ	2.56	2.25	0.21	1.72	3.05	5	0	36
JPM	4.62	3.80	0.37	2.95	5.25	4	0	59
MA	6.90	6.14	0.53	4.76	8.58	0	0	27
MO	2.71	2.60	0.26	1.85	3.22	22	0	44
MRK	2.90	2.80	0.25	1.77	3.98	10	0	40
MS	6.39	4.36	0.86	3.24	7.69	5	0	31
MSFT	5.35	5.03	0.29	3.96	6.04	2	0	62
NEM	3.39	3.67	0.39	2.11	4.62	7	0	28
NFLX	14.92	13.98	0.91	11.25	18.39	0	0	27
PFE	2.99	3.21	0.18	2.16	3.73	6	0	47
PG	3.45	2.91	0.27	2.34	4.08	2	0	52
QCOM	6.78	6.15	0.32	5.35	7.53	1	0	63
SHLD	7.76	7.86	0.55	5.20	8.84	0	0	27
T	3.40	2.79	0.42	2.27	3.80	6	0	35
UPS	3.53	3.38	0.45	2.14	4.25	4	0	28
VZ	2.95	2.84	0.28	1.95	3.74	7	0	36
WFC	5.90	3.86	1.06	3.10	5.34	0	0	31
WMT	3.26	3.30	0.15	2.60	3.57	3	0	51
X	6.75	6.44	0.61	5.64	7.68	2	0	27
XOM	2.50	2.28	0.21	1.80	3.20	11	0	51
YHOO	9.96	8.87	0.62	7.09	10.33	1	0	47

Table 5: **Anticipated uncertainty (term structure estimator, by calendar year)**

This table provides the average estimate of anticipated uncertainty $\sigma_j^{\mathbb{Q}}$ using the term-structure estimator $\sigma_{term}^{\mathbb{Q}}$. We report the summary statistics over the sample period from January 2000 until August 2015 for all firms in the sample and pool the results by calendar year. We report the mean, (Mean), median (Median), the standard error (Std Error), and the lower and upper quartile (25% and 75%) of all observations without errors. Err_1 counts the number of EAD on which the hypothesis of a decreasing term structure is violated, Err_2 counts the number of EAD on which the violations were more than 5% (i.e. $\sigma_{t,T_2} - \sigma_{t,T_1} > 0.05$). The last column provides the number of observations (Obs).

Term	Mean	Median	Std Error	25%	75%	Err_1	Err_2	Obs
2000	10.51	9.55	0.41	6.66	14.53	9	2	185
2001	10.91	10.76	0.45	6.13	14.78	13	0	190
2002	7.19	5.61	0.38	3.53	9.96	20	2	187
2003	4.90	4.78	0.18	2.90	6.53	31	2	194
2004	5.37	4.63	0.27	2.74	7.15	38	3	192
2005	5.13	4.47	0.24	2.81	6.88	30	1	195
2006	5.70	5.00	0.23	3.43	6.99	11	0	194
2007	5.95	5.21	0.25	3.49	7.37	16	0	189
2008	10.05	9.02	0.38	6.21	13.46	4	1	189
2009	7.01	6.18	0.34	3.96	9.37	12	0	188
2010	5.05	4.53	0.24	2.88	6.21	25	0	200
2011	6.16	5.11	0.31	2.83	8.11	15	1	200
2012	6.26	4.41	0.38	2.89	7.07	13	0	197
2013	6.83	5.13	0.33	3.60	8.86	3	0	198
2014	6.46	4.97	0.31	3.75	7.93	2	0	197
2015	5.93	4.99	0.29	3.32	7.82	3	1	149
Pooled	6.87	5.55	0.09	3.48	9.06	245	13	3008

smaller. Appendix A.5 provides further evidence on the errors and these results suggest that the majority of errors in the term structure estimator are driven by a combination of low earnings volatility, microstructure and/or data issues (e.g., stale quotes).

There is interesting time series variation in the earnings volatility estimates, summarized in Table 5. Earnings uncertainty was highest in recessions, 2000–2002 and 2008–2009, and was significantly lower in expansions. The magnitude of the effect is substantial: the average in 2000–2002 was more than double the average in tranquil years. This is consistent with higher earnings volatility, but also with an increase in the sensitivity of equity prices to earnings shocks (via a higher β in an earnings response model). These results complement Campbell *et al.* (2001) who show that both market and idiosyncratic volatility increase during periods of recession and Herskovic *et al.* (2016) who document a high degree of commonality in idiosyncratic volatility. Bloom (2009) finds that stock market volatility is strongly correlated with the cross-sectional spread of firm-level profit growth, our results imply that cross-sectional earnings uncertainty dispersion also increases in recessions. It is hard to identify these patterns in EA volatility using only realized equity returns and earnings, given there is only one noisy quarterly observation. Higher earnings volatility during recessions may also be related to leverage (e.g., Christie (1982)). In the compound pricing model of Geske (1979) equity volatility increases as the ratio of market value of debt to equity increases during recession. Similarly, if earnings announcements lead to jumps in the market value of the firm, EA volatility does increase with higher leverage. This is particularly true for firms with short-term maturity debt.[16]

Table 6 summarizes results for the time series estimator. The results are quantitatively and qualitatively similar to the term structure estimates. The average estimate is 6.04%, compared to 6.87% for the term structure estimator. As discussed earlier and in the Appendix, the time series estimator is likely to be downward biased relative to the term structure estimator. The two estimators do capture the quantitatively the same effect: the correlation between the time-series and term-structure estimates across firms is 93%.[17] To decompose the correlations further, column *Corr* in Table 6 provides the within firm, across time correlation between the term structure and time series estimates, conditional on both estimates being positive. These correlations are also high with a pooled Spearman coefficient of 82%. These findings provide strong evidence that the estimators are capturing a common effect,

[16] Geske *et al.* (2016) study the compound option model empirically, finding support for the impact of leverage on option prices.

[17] We use Spearman's rho to be robust with respect to outliers in the data. Results for Pearson's correlation are similar.

Table 6: **Anticipated uncertainty (time series estimator, by firm)**

This table provides anticipated uncertainty, $\sigma_j^{\mathbb{Q}}$, estimates using the time-series estimator $\sigma_{term}^{\mathbb{Q}}$. We report summary statistics over the sample period from 1/2000-8/2015 for all firms with at least seven years of EAD data. We report the mean, (Mean), median (Median), the standard error (Std Error), and the lower and upper quartile (25% and 75%) of all observations without errors. Err_1 counts the number of EAD on which the hypothesis of a decreasing implied volatility after the announcement is violated, Err_2 counts the number of EAD on which the violations were more than 5% (i.e. $\sigma_{\tau_j+1/252,T-1/252} - \sigma_{\tau_j-,T} > 0.05$). The column Corr provides rank correlations between the term-structure and time-series estimators of Table 4, the column No Data counts the number of EAD on which we cannot calculate the estimator due to missing option data. The last column provides the number of observations (Obs).

Time	Mean	Median	Std Error	25%	75%	Err_1	Err_2	Corr	No Data	Obs
AAPL	8.16	7.54	0.39	6.07	9.46	1	0	82.67	0	51
AIG	4.31	3.44	0.41	2.68	5.44	4	0	83.05	0	36
AMGN	4.73	4.20	0.38	3.35	6.11	1	0	49.13	1	40
AMZN	10.97	10.31	0.45	8.59	12.86	2	1	77.87	0	63
BA	3.74	3.66	0.29	2.86	4.62	5	0	9.71	0	27
BAC	3.29	2.68	0.33	1.87	4.14	12	2	28.07	0	51
C	2.43	2.23	0.15	1.70	2.91	13	2	33.63	0	47
CAT	4.97	4.22	0.34	3.74	5.56	2	0	66.41	0	46
COP	2.97	3.03	0.25	2.21	3.67	5	0	32.02	0	28
CSCO	7.58	7.29	0.34	5.97	8.34	1	0	77.07	0	60
CVX	2.06	1.95	0.17	1.43	2.39	10	0	41.42	0	36
DELL	6.14	6.28	0.28	5.40	7.08	2	1	21.35	0	28
EBAY	7.52	7.34	0.53	5.53	9.17	0	0	70.19	0	30
FCX	4.35	4.28	0.34	2.88	4.95	2	1	44.81	0	43
FSLR	12.90	13.03	0.69	10.03	14.85	1	1	83.39	0	27
GE	3.89	3.19	0.40	2.56	3.97	10	0	56.37	0	63
GOOGL	7.05	6.75	0.45	5.42	7.88	1	1	81.77	0	43
GS	4.30	3.45	0.35	2.76	5.15	2	0	69.39	0	55
IBM	5.18	4.60	0.21	4.31	5.53	1	0	73.31	0	63
INTC	6.17	5.69	0.28	4.81	6.73	2	0	66.51	0	62
JNJ	2.20	1.99	0.16	1.62	2.68	5	0	14.70	0	36
JPM	3.52	3.27	0.23	2.47	4.06	5	0	34.59	0	59
MA	5.83	5.39	0.51	4.02	8.04	1	0	87.67	0	27
MO	2.54	2.04	0.28	1.72	2.97	7	1	16.69	0	44
MRK	2.66	2.49	0.20	2.00	3.12	6	0	31.16	0	40
MS	4.42	3.90	0.53	2.97	5.11	5	2	29.25	1	31
MSFT	5.01	4.61	0.24	3.97	5.76	3	2	75.25	0	62
NEM	2.91	2.82	0.31	1.86	3.75	5	0	57.68	0	28
NFLX	12.91	12.24	0.86	9.99	16.73	1	1	81.20	0	27
PFE	2.74	2.99	0.16	1.96	3.41	8	2	22.32	0	47
PG	2.71	2.50	0.19	2.01	3.25	5	0	24.38	0	52
QCOM	6.79	6.09	0.40	5.13	7.40	2	0	68.38	1	63
SHLD	6.46	6.05	0.50	5.26	8.39	0	0	59.12	10	27
T	2.99	2.57	0.29	1.99	3.34	3	0	38.96	0	35
UPS	3.33	2.82	0.37	2.21	4.18	4	0	79.00	1	28
VZ	2.83	2.39	0.22	2.06	3.19	1	0	42.99	0	36
WFC	4.27	3.52	0.67	2.88	4.50	2	1	48.23	0	31
WMT	2.82	2.72	0.18	2.31	3.31	7	0	54.13	0	51
X	5.84	5.67	0.68	4.16	7.07	5	1	34.22	0	27
XOM	2.09	2.06	0.14	1.52	2.56	8	0	29.08	0	51
YHOO	8.71	7.70	0.62	6.02	10.37	1	0	62.12	0	47

both across firms and over time.

In terms of reliability, there are more error dates for the time series estimator, as expected from the discussion above. To see this, note first from the error columns in Table 6, there are more dates on which σ_{t,T_1} is substantially lower than $\sigma_{t+\Delta,T_1-\Delta}$ (where Δ is one trading day). Second, there are more dates on which we are unable to find pre/post EAD IVs for the same maturity, though these were concentrated in the beginning of the sample. Appendix A.3 and A.5 documents that firms with very high volatility or very low earnings volatility have noisier time series estimates. In what remains, we use only the more reliable and fully ex-ante term structure estimates.

4.4 Predictive Content of Anticipated Uncertainty

The next step is to understand the informational content of the ex-ante earnings price volatility measures. A large literature, cited earlier, finds that for individual firms, indices, currencies and other macroeconomic markets, option IV predicts subsequent realized return volatility, typically tested over horizons such as monthly. Our earnings jump volatilities correspond to shorter time horizons – daily or even overnight – for which it is more difficult to identify realized volatility predictors and the sampling problems are more severe.

Empirically, high $\mathbb{Q}$-Vol firms have high realized EAD volatility: the cross-sectional correlation between average EAD $\mathbb{Q}$ and $\mathbb{P}$-Vol is 85%. At the firm level, the time series correlation between the absolute EAD return $|r_j|$ (where r_j is the return from the close prior to the announcement to the first close after the announcement), and $\sigma_j^{\mathbb{Q}}$ (calculated using all available EADs for a given firm) is positive for all but three firms (see Table 7) with a highly significant averaged correlation of 53%. To understand the statistical properties of these results, suppose that $\log\left(\sigma_j^{\mathbb{Q}}\right) \sim \mathcal{N}\left(2, (0.25)^2\right)$, which generates an average anticipated

Table 7: **Predictive content of anticipated uncertainty**

This table provides correlations between anticipated uncertainty and the subsequent equity market return volatility for all firms with at least seven years of EAD data. *EAD Return abs* provides Pearson correlation coefficients and rank correlations and their corresponding p-values between $\sigma_j^{\mathbb{Q}}$ and the absolute return on the EAD. *EAD Return squared* provides the same statistics for the correlation between $\left(\sigma_j^{\mathbb{Q}}\right)^2$ and the squared return on the EAD.

Firm	**EAD Return abs**				**EAD Return squared**			
	Corr	p-val	RankCorr	p-val	Corr	p-val	RankCorr	p-val
AAPL	23.73	0.09	28.50	0.04	16.06	0.26	28.50	0.04
AIG	27.21	0.13	20.19	0.26	29.16	0.10	20.19	0.26
AMGN	56.14	0.00	44.50	0.01	54.81	0.00	44.50	0.01
AMZN	-2.09	0.87	3.61	0.78	-2.62	0.84	3.61	0.78
BA	25.48	0.22	13.92	0.51	35.83	0.08	13.92	0.51
BAC	89.40	0.00	59.82	0.00	98.52	0.00	59.82	0.00
C	34.15	0.03	33.51	0.03	39.66	0.01	33.51	0.03
CAT	13.46	0.37	13.60	0.37	6.45	0.67	13.60	0.37
COP	70.21	0.00	10.26	0.63	91.38	0.00	10.26	0.63
CSCO	23.64	0.07	10.92	0.41	26.29	0.04	10.92	0.41
CVX	0.05	1.00	-0.92	0.97	-3.88	0.85	-0.92	0.97
DELL	50.49	0.01	29.89	0.12	68.33	0.00	29.89	0.12
EBAY	-0.13	0.99	2.47	0.90	0.98	0.96	2.47	0.90
FCX	57.47	0.00	27.80	0.08	71.34	0.00	27.80	0.08
FSLR	-3.99	0.85	-0.03	1.00	-2.67	0.90	-0.03	1.00
GE	44.89	0.00	31.53	0.02	54.51	0.00	31.53	0.02
GOOGL	-2.40	0.88	-1.43	0.93	-3.73	0.81	-1.43	0.93
GS	54.79	0.00	23.58	0.09	69.45	0.00	23.58	0.09
IBM	31.46	0.01	17.88	0.16	36.23	0.00	17.88	0.16
INTC	32.03	0.01	28.20	0.03	23.71	0.06	28.20	0.03
JNJ	34.14	0.05	39.21	0.02	31.03	0.07	39.21	0.02
JPM	41.18	0.00	37.74	0.00	36.63	0.01	37.74	0.00
MA	64.01	0.00	50.67	0.01	70.71	0.00	50.67	0.01
MO	46.23	0.02	44.00	0.03	42.90	0.03	44.00	0.03
MRK	14.92	0.41	16.01	0.37	12.93	0.47	16.01	0.37
MS	28.57	0.14	11.99	0.54	27.72	0.15	11.99	0.54
MSFT	4.93	0.70	-10.40	0.42	25.52	0.05	-10.40	0.42
NEM	52.89	0.02	59.85	0.01	36.82	0.11	59.85	0.01
NFLX	13.01	0.52	2.38	0.91	16.26	0.42	2.38	0.91
PFE	4.15	0.79	-13.85	0.38	11.00	0.49	-13.85	0.38
PG	57.46	0.00	50.56	0.00	55.04	0.00	50.56	0.00
QCOM	17.53	0.18	5.69	0.66	25.96	0.04	5.69	0.66
SHLD	42.61	0.05	50.31	0.02	35.10	0.11	50.31	0.02
T	62.41	0.00	34.68	0.06	78.87	0.00	34.68	0.06
UPS	47.40	0.02	36.77	0.07	47.94	0.02	36.77	0.07
VZ	6.50	0.74	7.64	0.69	1.83	0.93	7.64	0.69
WFC	75.13	0.00	45.48	0.01	74.11	0.00	45.48	0.01
WMT	18.03	0.22	7.98	0.58	23.11	0.11	7.98	0.58
X	-0.38	0.99	10.35	0.63	-5.45	0.80	10.35	0.63
XOM	18.26	0.26	17.47	0.28	12.26	0.45	17.47	0.28
YHOO	39.28	0.01	23.80	0.11	38.73	0.01	23.80	0.11
Pooled	54.88	0.00	53.45	0.00	43.34	0.00	53.45	0.00

Table 8: **Predictive content of option implied diffusive and EAD jump volatility (pooled regression)**

This table provides results for cross-sectional regressions of EAD volatility variables on $\sigma_j^{\mathbb{Q}}$, diffusive equity volatility calculated from option prices and the standard deviation of EPS analyst forecasts (as reported in IBES) normalized by the equity price. We report regression coefficients for a range of different regression specifications and provide corresponding t-statistics in parentheses (we cluster standard errors by quarter and firm). Panel A provides regression results using the absolute EAD return as dependent variable, whereas Panel B uses the one-month equity volatility calculated from daily returns. Each observation corresponds to a unique earnings announcement, i.e. a unique firm-quarter observation.

	Model (1)		Model (2)		Model (3)		Model (4)	
Panel A – Dependent variable: absolute EAD return (close-to-close)								
Constant	0.01	(3.69)	0.05	(13.66)	0.02	(4.09)	0.01	(1.85)
EAD Jump Volatility	0.58	(11.42)					0.50	(7.02)
IBES Disagreement			0.82	(1.15)			-0.45	(-0.72)
Diffusive Volatility					0.09	(11.73)	0.03	(4.31)
R^2 (%)	28.47		0.17		15.28		29.68	
Panel B – Dependent variable: one-month standard deviation after EAD								
Constant	0.01	(9.74)	0.02	(12.72)	0.00	(2.30)	0.00	(0.30)
EAD Jump Volatility	0.26	(16.57)					0.12	(11.44)
IBES Disagreement			1.05	(3.42)			0.12	(0.96)
Diffusive Volatility					0.06	(16.98)	0.05	(16.24)
R^2 (%)	45.99		2.31		65.80		73.46	

uncertainty of about 7.4%, and that $r_j \sim \mathcal{N}\left(0, \left(\sigma_j^{\mathbb{Q}}\right)^2\right)$. Then, the population correlation between $|r_j|$ and $\sigma_j^{\mathbb{Q}}$ is about 30% and a 95% confidence interval is (0.01,0.57) for samples of our size. The range of values in Table 7 is entirely consistent with the model and normal sampling noise. Overall, our option-based EAD volatility estimators provide accurate and significant forecasts of the earnings announcement impact on equity prices.

Table 8 formalizes these results via cross-sectional regressions of absolute announcement day returns (close-to-close) on various variables. Panel A focuses on option-implied EAD jump volatility, diffusive volatility (also extracted from option prices) and the standard deviation of IBES EPS forecasts. Following DellaVigna and Pollet (2009) and others, the IBES analyst earnings uncertainty variable is constructed by standardizing EPS forecast volatility by the equity price ten days prior to the EAD. Results are based on all firm/quarter observations with a minimum analyst coverage of ten. Consistent with our firm-level results, $\sigma_j^{\mathbb{Q}}$ has considerable predictive power, with a highly significant β-coefficient (the t-statistic is 11.42) and an R^2 value of 28.47%. The IBES-based dispersion variable is insignificant and generates an $R^2 < 1\%$. The only other variable with predictive ability is the diffusive volatility prior to the EAD, though the R^2 increases by only 1% to 29.68% when including all three predictors. These results are robust.[18]

We provide additional results focusing on realized volatility over the month after an EAD. Our EAD-jump model predicts an increase in the impact of diffusive volatility over longer periods. Consistent with this, we find both option-implied variables are highly significant, although diffusive volatility is now more important. Diffusive IV explains almost 66% of the variation in a univariate regression, whereas the jump component explains 46%. Multivariate regressions confirm that the EAD-jump volatility provides significant incremental information about future realized volatility and is an important predictor of longer-term eq-

[18]First, we use different analyst dispersion estimates. The main results use equity-split adjusted statistics. Diether *et al.* (2002) argue this series can be inaccurate, especially when the reported volatility is low. Although not a major concern here, we also use unadjusted analyst-level data to construct forecast dispersion. Our methodology of aggregating the individual forecasts into summaries use several screens with respect to four criteria: (i) the forecasts are for the same firm and period, (ii) forecasts are issued before the IBES statistical period, (iii) they are not voided by the IBES data sets 'Excluded' or 'Stopped', and (iv) they are the most recent estimates issued by a broker once (i) to (iii) are satisfied. We apply the screens in three ways to aggregate the raw data into an analyst dispersion measure. For the first set of estimates, rules (i) and (ii) have to be fulfilled; for the second set rules (i), (ii), and (iv) have to be fulfilled; and for the third set of estimates all four must hold. Second, we alter the minimum number of analyst forecasts (up to a minimum of three). Third, we perform various sub-sample analyses. All of our conclusions are robust in sub-samples, and no findings change substantively across definitions. And forth, we estimate the HAR model of Corsi (2009) to predict one-day ahead daily variances and one-month ahead monthly variances using high-frequency data from the TAQ database rather than using implied volatility. Using these predicted variances as regressors instead of the diffusive part of the IVs does not change the significance of our EA jump measure. Overall, we find that – in line with a large existing literature – that the diffusive part of the option IVs is a better predictor than time-series based estimators from the HAR model.

Table 9: **Earnings announcement jump risk premia**

This table provides summary statistics on $\mathbb{P}$ and $\mathbb{Q}$-measure volatility on earnings announcement days. The second column (*Std*) provides the standard deviation of standardized equity returns the day after the earnings release, column $\mathbb{P}$-Vol (CC) provides the one-day close-to-close standard deviation of returns on earnings announcement days, $\mathbb{Q}$-Vol mean provides the risk-neutral counterpart. $\mathbb{P}$-Vol (CO) and $\mathbb{Q}$-Vol jump are based on close-to-open returns and the risk-neutral jump volatility $\sigma_j^{\mathbb{Q}}$, respectively. The last column provides estimates of the median of option-implied earnings announcement day volatility under $\mathbb{Q}$.

Year	Std	$\mathbb{P}$-Vol (CC)	$\mathbb{Q}$-Vol mean	$\mathbb{P}$-Vol (CO)	$\mathbb{Q}$-Vol jump	$\mathbb{Q}$-Vol median
2000 to 2005	0.94	7.63	9.92	6.65	7.46	7.08
2006 to 2010	0.92	7.22	7.74	5.60	6.77	6.15
2011 to 2015	0.91	7.35	6.78	6.60	6.34	5.19
Pooled	0.92	7.42	8.22	6.31	6.87	6.03

uity market volatility. Our findings are consistent with Athanassakos and Kalimipalli (2003) who argue that analyst dispersion has predictive power for monthly equity market volatility. Despite a highly significant slope coefficient, the explained variation of the analyst dispersion is low ($R^2 < 3\%$) and the coefficients are insignificant in multivariate regression.

4.5 Earnings Announcement Jump Risk Premiums

This section analyzes the EAD jump risk premium by comparing $\mathbb{P}$ and $\mathbb{Q}$-measure volatilities. Our model assumes continuously-compounded jumps under the $\mathbb{Q}$-measure are normally distributed with a volatility of $\sigma_j^{\mathbb{Q}}$, but places few restrictions on the behavior under $\mathbb{P}$. If there is a risk premium attached to the volatility of jump sizes, then $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$.[19]

We analyze this issue in three ways. First, we compare the realized volatility of returns under $\mathbb{P}$ with the average expected daily volatility of returns under $\mathbb{Q}$. To do this, we compute the expected one-day volatility under $\mathbb{Q}$ from option prices by adding to the EAD jump volatility one-day's diffusive volatility (denoted in Table 9 as $\mathbb{Q}$-Vol) and compare

[19]There is evidence for a diffusive volatility risk premium as well as some evidence for a risk premium attached to the volatility of jump sizes using index options, see Broadie *et al.* (2007).

this to the realized return volatility under $\mathbb{P}$ (denoted in Table 9 as $\mathbb{P}$-Vol). Test for equality across measures is difficult as both are estimated and time-varying. We first note that overall $\mathbb{Q}$-volatility is 80bps higher than $\mathbb{P}$-volatility on average, and the average $\mathbb{Q}$-volatility is larger than the average $\mathbb{P}$-volatility for most firms (untabulated), consistent with an earnings jump premium. These results could be sensitive to outliers, as mean estimates of $\sigma_j^{\mathbb{Q}}$ are higher than the median. Winsorized statistics (also untabulated) also indicate that $\mathbb{Q}$-Vol is higher than $\mathbb{P}$-Vol. A comparison of close-to-open return volatility under $\mathbb{P}$ with EAD jump volatility $\sigma_j^{\mathbb{Q}}$ also supports an economically sizable EAD volatility risk premium.[20]

A second, likely more powerful, statistic is the standard deviation of standardized EAD returns, $stdr_j = r_j / \sqrt{\left(\sigma_j^{\mathbb{Q}}\right)^2 + \sigma^2 \Delta}$, where Δ is one trading day. This accounts for time-varying volatility and is less sensitive to outliers. The standard deviation of $stdr_j$ equals one if there is no EAD jump risk premium. The column labeled *Std* in Table 9 provides additional evidence for an earnings jump volatility risk premium, as the pooled standard deviation is 0.92. The results are stable over the three subsamples with values ranging from 0.91 to 0.94. A chi-square test confirms that the standard deviations over the full sample period as well as over all sub-samples are significantly different from one at the 1% level. Overall, all tests point towards a positive and significant earnings jump volatility risk premium.

The third test computes straddle returns. If $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$, then writing straddles across EADs should be profitable. We calculate straddle returns from purchasing an ATM call and put at the close price prior to the earnings announcement and selling the position at the close after the announcement. To provide some intuition and to quantify the economic impact, consider an ATM call and straddle with one-week to maturity, an interest rate of 5% and $S_t = 25$. Prior to the announcement, call and put values were about \$1.53 and \$3.03, respectively. Assuming the equity price did not change the following day, the prices after

[20]We have also verified that splitting the close-to-close return into an overnight and intra-daily component and estimating the intradaily variance using a high-low variance estimator leads to identical conclusions.

Table 10: **Straddle returns**

This table provides summary statistics on the returns of at-the-money straddles that are held the day before an earnings announcement to the next trading day. We use options of the shortest available maturity (with at least three days to maturity on the first trading day after the earnings release). We report the mean (*Mean*), median (*Median*), standard deviation (*Std*), skewness (*Skewness*), kurtosis (*Kurtosis*) and the t-statistic (t-stat). The table also provides bootstrapped distributions for all statistics. For each bootstrap run, we select for each firm and announcement date in our sample a random date between 35 and 5 days prior to the announcement or 5 to 35 days after the announcement and calculate ATM straddle returns. The bootstrapped distributions are calculated from 250 samples.

Statistic	**Data**	**Bootstrapped Distribution**								
		mean	std	1%	5%	25%	50%	75%	95%	99%
Mean	-7.96	-1.51	0.29	-2.17	-1.94	-1.73	-1.52	-1.31	-1.01	-0.82
Median	-10.24	-3.17	0.21	-3.66	-3.50	-3.32	-3.17	-3.01	-2.86	-2.69
Std	27.47	15.01	0.70	13.68	13.97	14.54	14.95	15.28	16.39	17.32
Skewness	1.44	2.27	0.91	1.17	1.40	1.77	2.03	2.44	4.09	5.81
Kurtosis	8.93	21.77	19.64	8.65	9.84	12.92	15.75	20.90	61.27	113.18
t-stat	-13.25	-5.40	1.17	-7.92	-7.12	-6.19	-5.44	-4.60	-3.50	-2.63

the announcement fall to \$0.68 and \$1.65, respectively, an almost 50% decrease solely due to the drop in volatility from the EAD. If, however, the equity price fell 20% (a two standard deviation move), then the options are worth \$0.0 and \$5.03, respectively.

Table 10 reports an average one-day straddle return of -7.96% (across firm-quarter observations and not annualized), and a median return of -10.24%. Unreported robustness checks confirm these findings are consistent across time: straddle returns were negative during all 16 years in our sample and have (with one exception) highly significant t-statistics (-13.25 over the full sample period). The evidence for individual firms (also unreported) confirms that EAD straddle returns are on average significantly negative. There are only rare exceptions to this and the highest average firm-level return observed is merely 1%. Given the large realized volatilities of option strategy returns and the small sample size for individual firms, firm-level results can be quite sensitive to outliers and high idiosyncratic volatility.

To frame these results relative to our model, we also conduct a small scale Monte-Carlo experiment and simulate straddle returns using our reduced-form model of Section 2 for different values of $\sigma_j^{\mathbb{P}}$.[21] The results show that, for realistic parameter values, a wedge of 1% between real-world and risk-neutral EAD jump volatilities implies an average straddle return of -8.5% for options maturing one week after the EAD. Thus, our empirical straddle results are completely consistent with a reasonably parametrized jump-diffusion model and the results from our baseline model. We interpret this as strong evidence supporting $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$.

To further investigate significance, we perform a bootstrap experiment to understand the significance of straddle returns around EADs vis-a-vis normal trading days. Although unlikely given the mixed evidence regarding variance risk premiums in Carr and Wu (2009) and the large negative straddle returns, our results may be affected by the presence of a diffusive variance risk premium realized on non-EAD days. To this end, we simulate random samples as follows. For each firm and EAD, we randomly select a trading day within a symmetric 70 day window around the EAD (but excluding dates within 5 days of the EAD), which matches each EAD with a random day with similar overall market conditions. For a large number of random draws of these days for all firms/EADs, we calculate straddle returns and record return statistics. There are two noteworthy results (also reported in Table 10). First, straddle returns are substantially and statistically more negative on EADs than during normal market periods. The average straddle return of -7.96% compares to a 1%-percentile of only -2.17% on non-EAD trading days. And second, average straddle returns on non-EADs are negative providing new evidence for a negative variance risk premium and/or a risk premium attached to jump times and/or sizes.

Whether it is possible to devise profitable trading strategies to collect the earnings an-

[21] We use the same parameters as in Section 2.2 and assume that $\kappa_v = 3$ which implies an additional diffusive volatility risk premium. We randomize the variance before the announcement day by sampling its stationary distribution. We impose no risk premiums on Poisson jump risk. Our results are not sensitive to these choices.

nouncement volatility risk premiums depends crucially on trading costs. Table 1 suggests that naive trading strategies based on closing bid and ask quotes may consume a substantial portion of these short straddle returns. Muravyev and Pearson (2016) show that trading costs in option markets are, however, much lower than quoted bid-ask spreads. An empirical investigation of the impact of trade timing on the profitability of straddle returns around EADs is an interesting avenue for future research.

There are also theoretical arguments supporting non-zero EAD jump risk premiums. Jumps are difficult to hedge which could lead to a premium when combined with the demand-based arguments in Bollen and Whaley (2004). Garleanu *et al.* (2009) find that a combination of demand pressures and unhedgeable risks can create excess option IV. These results are also related to Ni *et al.* (2008), who analyze the volatility demand and predictable movements in realized and IV. As noted earlier, firms with higher EAD volatility have higher market exposure, which would also suggest a jump volatility risk premium (see also the learning based explanation in Savor and Wilson (2016) for an EAD mean risk premium).

4.6 Implications for Cross-sectional Studies

Equity IVs have recently been used in a number of empirical asset pricing studies, as regressors or for portfolio sorts. Since equity options that span EAs have significant IV variation unrelated to fundamentals, some of these sorts may be noisy. In this section, we replicate the results of Baltussen *et al.* (2016) (BBG hereafter) and test whether some of their conclusions may be strengthened by explicitly accounting for EAs. Finally, we provide guidance for empirical research using equity IV data.

BBG use short-term equity options to calculate the standard deviation of IVs over a calendar month. They show that high volatility of volatility (vol-of-vol) stocks underperform low vol-of-vol stocks by about 10 percent per year. Denoting the ATM IV at time t for stock i as $\sigma_{i,t}^{ATM}(T_e)$ (where $T_e > t$ is the fixed expiration date of the option), the authors define the vol-of-vol for stock i at time t as

$$VoV_{i,t} = \sqrt{\tfrac{1}{20}\sum_{j=t-19}^{t}\left(\sigma_{i,j}^{ATM}(T_e) - \bar{\sigma}_{i,t}^{ATM}(T_e)\right)^2} \times \left(\bar{\sigma}_{i,t}^{ATM}(T_e)\right)^{-1} \quad (6)$$

where

$$\bar{\sigma}_{i,t}^{ATM}(T_e) = \tfrac{1}{20}\sum_{j=t-19}^{t}\sigma_{i,j}^{ATM}(T_e). \quad (7)$$

For short-dated options, this vol-of-vol measure will be quite noisy and potentially biased during EA months. As the time to maturity decreases over time (i.e. $T_e - t$ decreases), option IVs exhibit a deterministic upward trend prior to EADs. Then, after the EAD, IVs drop immediately which will mechanically increases the vol-of-vol for announcing firms. The effects can be particularly large for firms with high earnings uncertainty and for short dated options. This suggests that if vol-of-vol is indeed a predictor of future stock returns, accounting for earnings announcement effects should remove noise in the portfolio sorts and strengthen BBG's main findings.

We replicate BBG's main analysis and form portfolios based on the VoV level. We obtain share prices from CRSP and (for comparison) restrict our sample from 1/1996 to 12/2009. We only retain stocks with share code 10 or 11 traded on either NYSE, NASDAQ or AMEX. We remove closed-end funds, REITs and stocks whose prices is \$5 or less. Furthermore, we discard small firms with market capitalization of \$225 million or less (in 2009 value). At the penultimate trading day in each month, we sort all remaining stocks into quintile portfolios based of VoV. Following BBG we use options that expire during the next trading month, which means that at the time of the sort, the options used in the calculation of

Table 11: **Quintile Portfolios of Stocks Sorted by Vol-of-Vol.**
The first portfolio (Low VoV) contains stocks with the lowest monthly Vol-of-Vol in the previous month and portfolio 5 (High VoV) contains stocks with the highest monthly Vol-of-Vol in the previous month. We equally-weight stocks in each quintile portfolio and rebalance monthly. For each portfolio columns (2) to (5) report the average raw returns, the CAPM and four-factor Fama-French-Carhart (FFC-4F) alphas. Panel A includes all stocks, Panel B uses only stocks with an earnings announcement during the portfolio formation month, whereas Panel C imposes the restriction that no earnings announcements occur during the portfolio formation month.

Panel A: Univariate Sort by VoV	Return	Excess Return	CAPM Alpha	FFC-4F Alpha
Low VoV	0.83	0.55	0.22	0.04
Q2	1.03	0.75	0.40	0.34
Q3	0.81	0.53	0.16	0.11
Q4	0.63	0.34	-0.05	-0.02
High VoV	0.21	-0.08	-0.51	-0.41
High minus Low Difference		-0.63	-0.73	-0.46
t-statistic		(-2.14)	(-2.76)	(-2.17)

Panel B: Univariate Sort by VoV (EA in formation month)	Return	Excess Return	CAPM Alpha	FFC-4F Alpha
Low VoV (EA in formation month)	0.31	0.02	-0.31	-0.55
Q2	0.87	0.59	0.25	0.20
Q3	0.99	0.71	0.35	0.37
Q4	0.53	0.25	-0.14	-0.08
High VoV (EA in formation month)	0.41	0.13	-0.26	-0.09
High minus Low Difference		0.11	0.04	0.45
t-statistic		(0.27)	(0.10)	(1.40)

Panel C: Univariate Sort by VoV (no EA in formation month)	Return	Excess Return	CAPM Alpha	FFC-4F Alpha
Low VoV (no EA in formation month)	1.04	0.76	0.43	0.28
Q2	1.03	0.74	0.38	0.29
Q3	0.96	0.68	0.30	0.24
Q4	0.76	0.47	0.08	0.07
High VoV (no EA in formation month)	-0.05	-0.33	-0.77	-0.71
High minus Low Difference		-1.09	-1.20	-0.99
t-statistic		(-3.61)	(-4.56)	(-4.04)

VoV have relatively short maturities (on average approximately one month). We then hold equally-weighted quintile portfolios during the next calendar month and rebalance monthly.

Panel A of Table 11 reports the results and confirms that the high-minus-low portfolio earns a negative CAPM alpha of -0.73% a month (BBG find a CAPM alpha of -0.50% with a t-statistic of -2.99). Note that our overall results differ marginally from BBG as our high-minus-low portfolio has a slightly larger return spread and quintile alphas are not completely monotone. Overall, our findings are quantitatively and qualitatively similar to BGG.

In Panel B, we restrict the portfolio sorts to firms which report earnings during the formation month. Since the exact timing of the EAD is not critical for this exercise, we rely on Compustat data for these announcements. As expected, results for this subset are quite different from the overall results in Panel A. We find no significant relationship between VoV and subsequent stock returns. In fact, excess returns and alphas now have opposite (positive) signs and are insignificant. In Panel C, results for the subset of stocks that do not announce earnings *strengthen* the overall conclusions in BBG as VoV is a stronger predictor when VoV is less noisy as return spreads and significance levels both increase. We repeat the analysis with value-weighted portfolio sorts and a range of different data filters and in all cases arrive at the same conclusions. We provide further evidence below which confirm that the insignificant return spreads in Panel B are due to the impact of EADs on IVs.

The empirical asset pricing literature considers a wide range of measures constructed from option prices and hence the impact of earnings announcements on empirical results may vary widely. And while it is difficult to provide general advice on how to deal with earnings announcements in empirical work, we can provide a list of important issues that should be considered when determining the impact of earnings releases on measures of equity IVs.

First, interpolated constant-maturity IVs have the advantage of removing the deterministic upward drift which is particularly pronounced in short-term options. Using interpolated data, measures based on IV changes may be constructed by removing only a handful of trading days: the EAD and potentially days on which the announcement enters the calculation for the first time. Despite the widespread use of interpolated IVs from OptionMetrics, it is also worth noting, however, that OptionMetrics interpolated volatilities and use a log transformation of the time to maturity in their interpolation method. Our model-based results imply that the most reasonable interpolation is linear in variances (as for instance in Carr and Wu (2009)).

Second, depending on the application, it may be useful to separate diffusive and EAD jump volatility (as we do in Section 3). While this approach has theoretical advantages, it requires the earnings dates and times and may suffer from noise due to database errors and missing EAD information. Third, an important consideration is the choice of option maturity. While many studies rely on short term IVs due to higher liquidity and trading volume, longer term IVs are far less affected by EAs than short-term options. For instance, when we repeat the analysis of BBG with longer-term options, we find that the difference between announcing firms and non-announcing firms narrows substantially and that the vol-of-vol effect exhibits the same sign in both groups with only minor differences in the alphas for the spread portfolios. For instance, using options with one year to maturity, the CAPM alpha of the high-minus-low portfolio for announcing firms is -0.81% compared to -0.79% for non-announcing firms (untabulated). This result is theoretically expected and supports our claim that earnings releases are the main driver of the empirical results in Panel B of Table 11. Depending on the research question, longer dated IVs may be sufficient. Finally, it is essential to provide robustness checks by removing EADs and/or announcing firms unless the research question explicitly deals with earnings announcements. Han and Zhou (2012) and Vasquez (2015) for example split the sample into announcing and non-announcing firms (as we do in this section). Earnings announcements are not only important because of the variation they cause in IVs, but they also affect returns through different channels (Beaver (1968), Cohen *et al.* (2007), Frazzini and Lamont (2007) and Savor and Wilson (2016)).

4.7 Option Pricing Implications

This section analyzes earnings jumps in standard SV models with randomly timed jumps in prices. This allows us to quantify the economic impact on option prices and compare the impact of EAs to other components such as randomly timed jumps.

The literature on individual equity options is relatively small compared to the literature on index options. One reason for this is the computational difficulty present in calibrating SV models on many firms. Bakshi *et al.* (2012) study the performance of option pricing specifications nested in the double jump model of Duffie *et al.* (2000) and conclude that "in contrast to index-options, [jump] model generalizations are unable to produce a large improvement for near-the-money individual equity options." They find that there is greater improvement for deep OTM options. Further studies on individual equity options include Christoffersen *et al.* (2015), who model the joint dynamics of index and individual equity options, and Carr and Wu (2016), who propose a self-exciting jump model and estimate it on equity options of five individual firms. This paper is the first to explicitly account for earnings announcements in the data-generating process and to quantify the impact.

We consider a number of nested versions of the earnings jump model developed in Section 2: SVJEJ is the full specification with SV, randomly timed jumps and earnings jumps; SVJ is the model without EAD jumps; SVEJ is the model with earnings jumps; and SV is a purely diffusive SV model. For all four models, we estimate the parameters and filter the latent variance process using the unscented Kalman filter of Julier and Uhlmann (1997) and Wan and Van Der Merwe (2000).[22] To describe our approach, let $IV\left(S_t, V_t, \Upsilon^{\mathbb{Q}}, T_n, K_n\right)$ denote the model-based IV of an option with strike K_n and time to maturity T_n, and let $\Upsilon^{\mathbb{Q}} = \left(\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}, \sigma_v, \rho, \widehat{\sigma}^{\mathbb{Q}}, \bar{\lambda}^{\mathbb{Q}}, \bar{\mu}_y^{\mathbb{Q}}, \bar{\sigma}_y^{\mathbb{Q}}\right)$ denote the structural parameters. For simplicity we assume that the EAD jump volatility $\sigma_j^{\mathbb{Q}}$ is constant over time, i.e. $\sigma_j^{\mathbb{Q}} = \widehat{\sigma}^{\mathbb{Q}}$ for all j, and hence our deterministic jump models require only one additional parameter. Extensions to time-changing jump volatilities are left to future research.

The observation equation is given by

$$IV_t^m(T_n, K_n) = IV\left(S_t, V_t, \Upsilon^{\mathbb{Q}}, T_n, K_n\right) + e_{t,n} \qquad \forall n = 1, \ldots, n_t,\ t = 1, \ldots, T \tag{8}$$

where IV_t^m is the observed IV at time t and n_t is the number of options available at time t.[23] The error term $e_{t,n}$ is assumed to be i.i.d. normal with mean zero and standard deviation σ_e. The state evolution is given by a time discretization of the $\mathbb{P}$-dynamics of the square-root variance process. This approach provides estimates of the spot variances, the SV and jump parameters under the $\mathbb{Q}$-measure, and the $\mathbb{P}$-measure parameters of the SV process.

We construct a sample of option prices by averaging the IV for the put/call option pair closest to the money for each maturity and day and also for the option pairs with moneyness closest to 0.90 and 1.10. To our knowledge and due to computational burdens, few calibration procedures use daily data over long time samples, most studies focus on weekly data (see

[22]This procedure imposes that the model parameters remain constant during the whole sample period. Ideally, one would estimate the model using, in addition to option prices, the time series of returns. Other approaches include EMM (Chernov and Ghysels (2000)), implied-state GMM (Pan (2002)), MCMC (Eraker (2004)), or the approximate MLE approach of Aït-Sahalia and Kimmel (2007). These approaches are in principle statistically efficient, however the computational demands of pricing options for each simulated latent volatility path and parameter vector constrains research short data samples and/or few options contracts (typically one per day).

[23]See Christoffersen and Jacobs (2004) for a discussion of choice of loss function.

for instance Bates (2000), Christoffersen *et al.* (2010) or Andersen *et al.* (2015)).[24] For our sample, the computational burden of using daily data, multiple options and several firms is extreme: we have to numerically compute around 150,000 option prices for each objective function evaluation. Due to these computational burdens, we restrict our empirical analysis to all firms that remain in our sample throughout entire period: AMZN, GE, IBM, INTC, MSFT, and QCOM.[25] These firms vary substantially in terms of the earnings jump volatilities reported in Section 4.3.

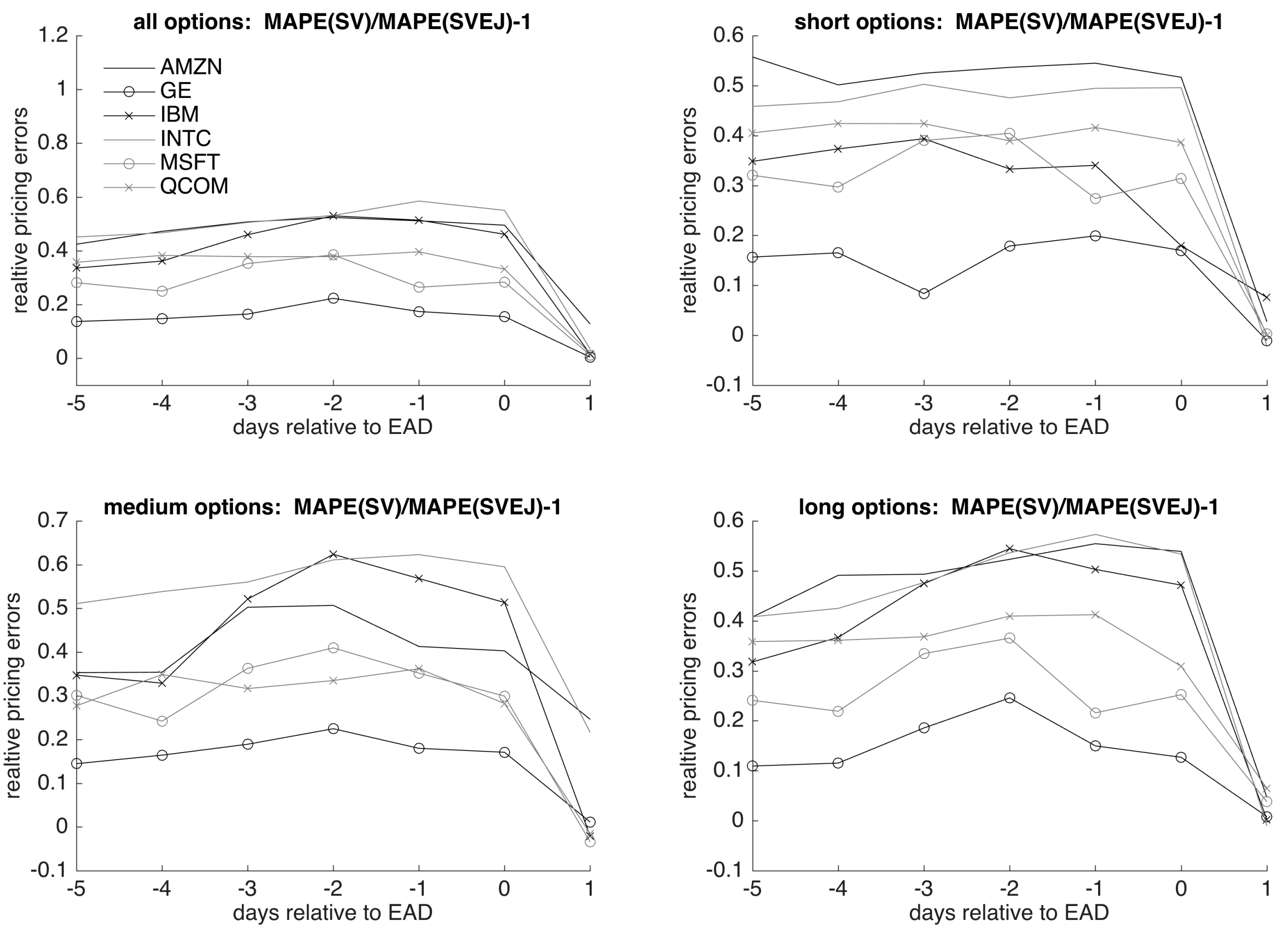
To understand the impact of earnings jumps, consider first option pricing errors as a measure of overall fit. Figure 2 provides the difference between the average absolute IV pricing errors for SV and SVEJ for the days surrounding EADs, in addition to pricing errors by option maturity. To economize on space, we focus on SV and SVEJ and provide detailed results for other models upon request. Accounting for jumps on EADs leads to a significant pricing improvement: in the week before an EAD, overall pricing errors across all firms can fall by more than 50%, the errors fall in all cases. To provide further intuition, for Intel the mean absolute pricing errors fall in the three days prior to earnings announcements from 4.111, 3.911 and 4.554 in the SV model to 1.925, 1.623 and 2.047 in the SVEJ model, respectively (untabulated). The earnings announcement effect is most pronounced in short-dated options, given their sensitivity to earnings jumps, but there is also a significant improvement in long-dated option prices. In SV models, IVs are only driven by spot volatility, V_t, and, intuitively, if spot volatility increases enough to match short-dated IVs, it will massively overshoot longer-dated IVs, a tension released by accounting for earnings jumps. Although

[24] Pan (2002) uses two option prices sampled weekly over a five year period, Eraker (2004) uses a single option price for every day over a four year period.

[25] Additionally we estimate all structural models for all firms that are missing only during one year: Cisco Systems (CSCO), Goldman Sachs (GS), JP Morgan/Chase Manhattan Bank (JPM), Wal-Mart Stores (WMT) and Apple (AAPL), which is missing during two years. Due to space restrictions, we do note report these additional results which are qualitatively and quantitatively very similar to the results presented in this section.

Figure 2: **Pricing Errors Around Earnings Announcement Days**

This figure reports the relative difference between the mean absolute pricing errors of the SV and SVEJ model on trading days around earnings announcements: $\mathrm{MAPE}(SV)/\mathrm{MAPE}(SVEJ)-1$, where $\mathrm{MAPE}(M)$ denotes the mean absolute pricing error of model M. The data set is a representative daily option sample from January 2000 to August 2015. Pricing errors are grouped into four different categories: all (all options), short (less than 30 days to maturity), medium (between 31 and 90 days to maturity) and long (more than 90 days to maturity). We report estimation results for Amazon (ticker: AMZN), General Electric (GE), Intel Corporation (INTC), International Business Machines Corporation (IBM), Microsoft (MSFT) and Qualcomm (QCOM). For exact model definitions see Section 2 and 4.7.



not reported, models incorporating randomly timed jumps do not add any further pricing improvements around EADs (we provide further details below).

Table 12 provides pricing errors by moneyness and maturity. In addition to the four SV-based models, for comparison we also provide pricing errors for the Black-Scholes model augmented with earnings jumps (BSEJ). We estimate pricing errors for this model by simply minimizing the squared pricing errors between model and IV.[26] We classify options according to their moneyness (OTM, ITM or ATM) and use three different maturity categories. There is a substantial pricing improvement for all firms and categories. For intel, the improvement is 36%, 14%, and 24%, respectively, for the three maturity categories. SVEJ also offers sizeable improvements for ATM options with errors decreasing from 1.81 to 1.40. Our results contrast with Bakshi *et al.* (2012) who find that randomly timed jumps in prices or in volatility provide little benefit for pricing ATM options. Overall, our results indicate that incorporating jumps on EADs provides first order pricing improvements not only around EADs, but over the entire sample.

Table 13 summarizes fits and parameter estimates for each of the four models. Overall, we find strong evidence for earnings jumps, as well as evidence for leverage effects and randomly timed jumps in returns. In terms of model fits, the final column shows the incremental improvements for each of the components and our results indicate that earnings jumps are far more important than randomly timed price jumps. For example, for Intel, σ_e is 3.34%, 2.54%, 3.28%, and 2.52% for SV, SVEJ, SVJ, and SVJEJ models, respectively, indicative of a modest improvement of randomly timed jumps and a larger improvement of earnings jumps. This result is consistent across firms, and even firms with low anticipated uncertainty on

[26]In order to estimate errors, we first fix an earnings jump parameter and optimize on each trading day the diffusive volatility which implies a daily recalibration of the diffusive volatility. We then alternate the earnings jump parameter until an optimum is found. Note that the BSEJ model is less constrained in its minimization of pricing errors as we do not filter the variance path for this model. In addition BSEJ is calibrated using an option pricing error metric whereas the unscented Kalman filter used for the other models includes both a likelihood term for the variance path and observed option prices.

Table 12: **Option pricing error by moneyness and maturity**

This table reports the mean absolute pricing errors for the BSEJ, SV, SVEJ, SVJ and SVJEJ models. The data set is a representative daily option sample from January 2000 to August 2015. Pricing errors are grouped into six different categories: OTM (if $M < 0.95$), ATM (if $0.95 \leq M \leq 1.05$), ITM (if $M > 1.05$), short (less than 30 days to maturity), medium (between 31 and 90 days to maturity) and long (more than 90 days to maturity). We report estimation results for Amazon (ticker: AMZN), General Electric (GE), Intel Corporation (INTC), International Business Machines Corporation (IBM), Microsoft (MSFT) and Qualcomm (QCOM). For exact model definitions see Section 2 and 4.7.

Firm	Model	Option Categories						
		All	OTM	ATM	ITM	short	medium	long
AMZN	BSEJ	2.40	2.84	1.88	2.51	3.40	2.00	2.03
	SV	2.66	2.73	2.63	2.61	3.92	2.35	2.15
	SVEJ	1.99	2.10	1.87	2.01	2.95	1.55	1.70
	SVJ	2.59	2.61	2.61	2.56	3.75	2.29	2.16
	SVJEJ	1.94	1.98	1.90	1.93	2.83	1.48	1.71
GE	BSEJ	2.22	2.85	1.51	2.46	3.61	2.31	1.77
	SV	1.60	1.80	1.40	1.65	2.87	1.49	1.28
	SVEJ	1.51	1.68	1.33	1.56	2.70	1.38	1.23
	SVJ	1.55	1.61	1.46	1.62	2.77	1.41	1.26
	SVJEJ	1.51	1.61	1.36	1.58	2.61	1.38	1.24
IBM	BSEJ	2.21	2.77	1.52	2.46	3.42	1.95	1.71
	SV	1.93	2.16	1.74	1.91	2.84	1.39	1.69
	SVEJ	1.61	1.75	1.45	1.67	2.44	1.20	1.41
	SVJ	1.79	1.91	1.72	1.73	2.71	1.24	1.58
	SVJEJ	1.51	1.61	1.43	1.52	2.30	1.14	1.32
INTC	BSEJ	2.10	2.55	1.58	2.23	3.51	1.87	1.68
	SV	1.88	1.97	1.81	1.85	3.28	1.47	1.49
	SVEJ	1.49	1.55	1.40	1.55	2.70	1.18	1.21
	SVJ	1.82	1.84	1.82	1.81	3.17	1.40	1.46
	SVJEJ	1.48	1.49	1.44	1.52	2.64	1.15	1.21
MSFT	BSEJ	1.94	2.40	1.40	2.11	3.10	1.80	1.60
	SV	1.61	1.73	1.47	1.64	2.76	1.30	1.35
	SVEJ	1.46	1.59	1.29	1.52	2.52	1.18	1.23
	SVJ	1.54	1.60	1.46	1.57	2.56	1.22	1.33
	SVJEJ	1.42	1.50	1.31	1.47	2.38	1.12	1.24
QCOM	BSEJ	2.31	2.79	1.68	2.53	3.54	1.98	1.87
	SV	1.92	2.06	1.76	1.98	3.12	1.45	1.62
	SVEJ	1.68	1.82	1.46	1.78	2.73	1.22	1.43
	SVJ	1.87	1.97	1.74	1.94	2.99	1.43	1.58

Continued on next page

Table 12 – continued from previous page

Firm	Model	Option Categories						
		All	OTM	ATM	ITM	short	medium	long
	SVJEJ	1.66	1.76	1.49	1.74	2.61	1.22	1.44

Table 13: **Parameter estimates.**

This table reports the estimation results for the SV, SVEJ, SVJ and SVJEJ models. The parameters are estimated using the unscented Kalman filter on a representative daily option sample from January 2000 to August 2015. For each parameter, we report estimates and asymptotic standard errors in parenthesis. We report estimation results for Amazon (ticker: AMZN), General Electric (GE), Intel Corporation (INTC), International Business Machines Corporation (IBM), Microsoft (MSFT) and Qualcomm (QCOM). For exact model definitions see Section 2 and 4.7.

Firm	κ_v	θ_v	σ_v	ρ	$\kappa_v^{\mathbb{Q}}$	$\theta_v^{\mathbb{Q}}$	$\bar{\lambda}_y^{\mathbb{Q}}$	$\bar{\mu}_y^{\mathbb{Q}}(\%)$	$\bar{\sigma}_y^{\mathbb{Q}}(\%)$	$\widehat{\sigma}^{\mathbb{Q}}(\%)$	$\sigma_e(\%)$
AMZN	1.28	0.36	0.80	-0.55	0.88	0.28					3.91
	(0.25)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)					(0.01)
	1.28	0.36	0.77	-0.63	0.73	0.21				8.77	3.24
	(0.23)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)				(0.02)	(0.00)
	0.89	0.12	0.94	-0.85	0.52	0.31	38.28	-0.49	3.85		3.81
	(0.13)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)	(0.06)	(0.00)	(0.01)		(0.00)
	1.15	0.36	0.76	-0.89	0.60	0.18	6.70	-0.17	7.33	8.70	3.13
	(0.04)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.02)	(0.00)
GE	3.22	0.10	0.98	-0.43	0.85	0.14					2.57
	(0.51)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)					(0.00)
	3.46	0.10	1.11	-0.45	0.53	0.21				2.95	2.44
	(0.73)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)				(0.01)	(0.00)
	0.69	0.05	0.86	-0.65	0.72	0.10	4.59	0.10	5.60		2.50
	(0.34)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
	0.63	0.06	0.78	-0.66	0.85	0.09	0.69	0.34	13.02	2.86	2.41
	(0.33)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.01)	(0.00)
IBM	4.07	0.09	1.00	-0.44	1.70	0.09					3.21
	(0.83)	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)					(0.00)
	0.75	0.12	1.07	-0.47	1.16	0.10				4.15	2.59
	(0.65)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)				(0.00)	(0.00)
	1.75	0.04	0.81	-0.69	1.29	0.05	6.59	-1.17	5.62		3.01
	(0.46)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)		(0.00)
	0.75	0.09	0.62	-0.78	1.16	0.05	2.30	-1.52	7.40	4.03	2.46
	(0.12)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
INTC	2.68	0.17	0.96	-0.38	1.46	0.13					3.34
	(0.55)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)					(0.00)
	1.78	0.16	0.88	-0.47	1.05	0.13				5.07	2.54
	(0.63)	(0.05)	(0.01)	(0.00)	(0.01)	(0.00)				(0.00)	(0.00)

Continued on next page

Table 13 – continued from previous page

Model	κ_v	θ_v	σ_v	ρ	$\kappa_v^{\mathbb{Q}}$	$\theta_v^{\mathbb{Q}}$	$\bar{\lambda}_y^{\mathbb{Q}}$	$\bar{\mu}_y^{\mathbb{Q}}(\%)$	$\bar{\sigma}_y^{\mathbb{Q}}(\%)$	$\widehat{\sigma}^{\mathbb{Q}}(\%)$	$\sigma_e(\%)$
	0.63	0.11	0.90	-0.65	1.16	0.09	9.67	-0.10	5.45		3.28
	(0.40)	(0.07)	(0.00)	(0.00)	(0.01)	(0.00)	(0.08)	(0.01)	(0.02)		(0.00)
	0.63	0.14	0.76	-0.71	0.97	0.10	4.16	0.10	6.26	5.01	2.52
	(0.27)	(0.06)	(0.00)	(0.01)	(0.01)	(0.00)	(0.07)	(0.00)	(0.06)	(0.00)	(0.00)
MSFT	2.20	0.11	0.76	-0.39	1.04	0.11					2.64
	(0.69)	(0.04)	(0.01)	(0.00)	(0.01)	(0.00)					(0.00)
	2.23	0.11	0.82	-0.41	0.74	0.13				3.93	2.39
	(0.33)	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)				(0.00)	(0.00)
	0.63	0.06	0.65	-0.72	0.85	0.08	6.43	0.05	5.72		2.54
	(0.22)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)		(0.00)
	0.75	0.07	0.61	-0.74	0.79	0.08	3.01	0.24	7.11	3.79	2.32
	(0.34)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.01)	(0.00)	(0.00)
QCOM	0.68	0.36	0.86	-0.47	0.71	0.23					3.01
	(0.16)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)					(0.00)
	0.53	0.34	0.89	-0.52	0.56	0.25				5.02	2.72
	(0.10)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)				(0.01)	(0.00)
	0.05	0.16	0.79	-0.67	0.53	0.21	5.16	-0.69	6.78		2.92
	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.03)		(0.00)
	0.52	0.22	0.74	-0.70	0.56	0.18	2.22	-1.12	8.89	4.92	2.65
	(0.09)	(0.04)	(0.00)	(0.01)	(0.00)	(0.00)	(0.04)	(0.02)	(0.10)	(0.01)	(0.00)

EADs (General Electric for example) provide evidence if favor of SVEJ over a random jump model. Although not reported, a likelihood ratio test overwhelmingly rejects the restrictions that jump volatilities are zero.[27]

In terms of earnings jump estimates, we focus on $\widehat{\sigma}^{\mathbb{Q}}$ and use Intel as an example. The average jump volatility for Intel from the term structure and time series estimator was 7.04 and 6.17, respectively. The estimates using the formal SV model extensions are similar, although values are lower with slightly more than 5%. Similar results are obtained for the other firms. There are at least two reasons why these estimates may differ. First, the time-series and term-structure estimators of the previous section use one and two options,

[27] Our primary goal is to quantify the pricing improvements generated by jumps on EADs. Although common in the literature, we do not perform an out-of-sample pricing exercise. As noted in Bates (2003), these tests, in general, are not particularly useful for analyzing model specification: "*Perhaps the one test that does not appear to be especially informative is short-horizon "out-of-sample" option pricing tests...*" (p. 396).

respectively, whereas the full estimation results use information contained in all options that are affected by earnings announcement jumps. This means that on each day at least three options are affected and an earnings announcement will have a significant impact on options for at least a month prior to the announcement. If investor's perceptions of $\widehat{\sigma}^{\mathbb{Q}}$ changes in the days and weeks prior to the earnings announcement, this would result in slightly lower estimates. And second, the SV model imposes that the parameters in the model are constant through time, whereas the term-structure and time-series estimators allow volatility to differ at each announcement. Due to this, the estimates based on the extension of the Black-Scholes model are less constrained and less subject to potential misspecification. For robustness, we have experimented with additional calibration methodologies and find that our EA jump volatility estimators are indeed very close if the same option data is used in the estimation. Provided our estimation routine provides a lower bound, the impact of EAs on option pricing applications that we report is conservative. Further discussion of structural model parameters is relegated to Appendix A.7.

5 Conclusions

This paper develops models incorporating earnings announcements for pricing options and for learning about the uncertainty embedded in an individual firm's earnings announcement. We take into account the timing of earnings announcements and develop a model and pricing approach incorporating jumps on EADs. We introduce estimators of the uncertainty surrounding earnings announcements and discuss the general properties of models with deterministically-timed jumps. Empirically, we find strong evidence that earnings announcements are important components of option prices, we investigate risk premiums, and we analyze the underlying assumptions of the model. To quantify the impact on option prices, we calibrate a SV model and find that accounting for jumps on EADs is extremely important for pricing options. Models without jumps on EADs have large and systematic pricing errors around earnings dates. A SV model incorporating earnings jumps drastically lowers the pricing errors and reduces misspecification in the volatility process.

There are a number of interesting extensions. First, we are interested in understanding the ex ante information in macroeconomic announcements. Ederington and Lee (1996) and Beber and Brandt (2006) document a strong decrease in IV subsequent to major macroeconomic announcements, which is the same effect we document for earnings announcements.[28] Second, it would be interesting to explore how investors form expectations about anticipated earnings uncertainty and timing of information gathering.

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A Online Appendix

A.1 Transform Analysis

This section provides details on the option transforms. To price options, we need to evaluate the conditional transform of $\log(S_T)$. In our framework, the logarithm of the stock price consists of two independent, additive components. First, an affine process for which the characteristic function is well-defined and provided in Duffie *et al.* (2000). The second component is a simple discrete process with deterministic jumps at known times. Since the two components are independent, the characteristic function of the log stock price is given by the product of the characteristic functions of the two components. It follows that the discounted transform for $c \in \mathbb{C}$ is exponentially affine:

$$\begin{aligned}
\Psi(c, S_t, V_t, t, T) &= E_t^{\mathbb{Q}}\left[\exp(-r(T-t))\exp(c \cdot \log(S_T))\right] \\
&= \exp\left(\alpha(c,t,T) + \beta(c,t,T)V_t + c \cdot \log(S_t)\right)
\end{aligned}$$

where $\beta(c,t,T)$ and $\alpha(c,t,T)$ are given by

$$\begin{aligned}
\beta(c,t,T) &= \frac{c(1-c)\left[1-e^{\gamma_v(T-t)}\right]}{2\gamma_v - \left(\alpha_v - \kappa_v^{\mathbb{Q}}\right)\left[1-e^{\gamma_v(T-t)}\right]} \\
\alpha(c,t,T) &= \alpha^*(c,t,T) + \overline{\alpha}(c,t,T) + \sum_{j=N_t^d+1}^{N_T^d}\left(-\frac{c}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2 + \frac{c^2}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2\right)
\end{aligned}$$

with

$$\begin{aligned}
\alpha^*(c,t,T) &= r\tau(c-1) + \frac{-\kappa_v^{\mathbb{Q}}\theta_v^{\mathbb{Q}}}{\sigma_v^2}\left[\left(\alpha_v - \kappa_v^{\mathbb{Q}}\right)\tau + 2\ln\left(1 - \frac{\alpha_v - \kappa_v^{\mathbb{Q}}}{2\gamma_v}\left(1-e^{\gamma_v\tau}\right)\right)\right], \\
\overline{\alpha}(c,t,T) &= \bar{\lambda}_y^{\mathbb{Q}}\tau\left[e^{\bar{\mu}_y^{\mathbb{Q}}c + \frac{1}{2}\left(\bar{\sigma}_y^{\mathbb{Q}}\right)^2 c^2} - 1\right] - \bar{\lambda}_y^{\mathbb{Q}}\tau\left[e^{\bar{\mu}_y^{\mathbb{Q}} + \frac{1}{2}\left(\bar{\sigma}_y^{\mathbb{Q}}\right)^2} - 1\right],
\end{aligned}$$

$\tau = T - t$, $\gamma_v = \left[\left(\sigma_v \rho c - \kappa_v^{\mathbb{Q}}\right) + c\left(1-c\right)\sigma_v^2\right]^{1/2}$ and $\alpha_v = \gamma_v + \sigma_v \rho c$.

The transform with deterministic jumps has a particularly simple structure under our assumptions. To see this, note that

$$\begin{aligned}
\log\left(S_T\right) &= \log\left(S_t\right) + \int_t^T \left(r - \tfrac{1}{2}V_s - \bar{\lambda}_y^{\mathbb{Q}} E_t^{\mathbb{Q}}\left[e^{\bar{Z}_j(\mathbb{Q})} - 1\right]\right) ds + \int_t^T \sqrt{V_t} dW_t^s(\mathbb{Q}) \\
&\quad + \sum_{j=\bar{N}_t(\mathbb{Q})+1}^{\bar{N}_T(\mathbb{Q})} \bar{Z}_j(\mathbb{Q}) + \sum_{j=N_t^d+1}^{N_T^d} Z_j(\mathbb{Q}) \\
&= \log\left(\widetilde{S}_T\right) + \sum_{j=N_t^d+1}^{N_T^d} Z_j(\mathbb{Q})
\end{aligned}$$

where $\log\left(\widetilde{S}_T\right)$ is the standard affine component. Assuming deterministic jumps are conditionally independent of the affine state variables, the transform of $\log\left(S_T\right)$ is just the product of the traditional affine transform and the transform of the deterministic jumps:

$$\begin{aligned}
&E_t^{\mathbb{Q}}\left[\exp\left(-r\left(T-t\right)\right)\exp\left(c \cdot \log\left(S_T\right)\right)\right] \\
&\quad = E_t^{\mathbb{Q}}\left[\exp\left(-r\left(T-t\right)\right)\exp\left(c \cdot \log\left(\widetilde{S}_T\right)\right)\right] E_t^{\mathbb{Q}}\left[\exp\left(c \sum_{j=N_t^d+1}^{N_T^d} Z_j(\mathbb{Q})\right)\right] \\
&\quad = \exp\left[\alpha\left(t\right) + \beta\left(t\right) \cdot V_t + c \cdot \log\left(S_t\right)\right]\exp\left(\alpha^d\left(t\right)\right)
\end{aligned}$$

where $E_t^{\mathbb{Q}}\left[\exp\left(c \sum_{j=N_t^d+1}^{N_T^d} Z_j(\mathbb{Q})\right)\right] = \exp\left(\alpha^d\left(t\right)\right)$ for some state-independent function α^d, $\alpha^*\left(t\right) = \alpha^*\left(c,t,T\right)$, and $\beta\left(t\right) = \beta\left(c,t,T\right)$. This implies that only the constant term in the exponential is adjusted. Thus, option pricing with earnings announcements requires only minor modifications of existing approaches.

Our model structure is particularly simple as deterministic jumps do not affect the persistent stochastic volatility process which is completely independent of the jump. In a recent paper, Kim and Wright (2014) propose multi-factor term-structure models with deterministic jumps in the state variables on economic announcement days. In their model, the deterministic jump leads to time-inhomogeneous ODEs as the jump in a mean reverting process affects the mean-reversion behavior after the announcement and hence one has to account for this additional feature.

A.2 Black-Scholes and Stochastic Volatility

This appendix analyzes the impact of SV on the earnings announcement jump estimators. Standard SV models imply that volatility has predictable components and potentially large and asymmetric shocks. The time series and term structure estimators formally assume a constant expected diffusive volatility, which could result in a systematic bias.

The first issue can be addressed using the insights of Hull and White (1987) and Bates (1996). Under mild conditions on SV, if shocks to volatility and returns are independent, then the SV option price is the expectation of the Black-Scholes price where the Black-Scholes implied variance is the expected integrated risk-neutral variance $EIV_{t,T} = E_t^{\mathbb{Q}}\left[\int_t^{t+T} V_s ds\right]$. Based on this, it is common to assume that Black-Scholes implied variance is an accurate proxy for expected risk neutral variance, that is, $\left(\sigma_{t,T}^{BS}\right)^2 \approx EIV_{t,T}$. The errors in assuming that $\left(\sigma_{t,T}^{BS}\right)^2 \approx EIV_{t,T}$ are generally small for ATM index options, and will be even smaller for individual equity options. For ATM options, Hull and White (1987) find the errors are less than 1% with no leverage and only 1.6% when $\rho = -0.6$. The errors are even smaller for shorter maturities which we use in our empirical analysis. Of course, approximation errors can be quite large for out-of-the-money options.

Price jumps also do not lead to a substantial bias. Merton (1976) finds that the errors of using the Black-Scholes model with a properly adjusted variance are extremely small for

ATM options.[29] Chernov (2007) quantifies the approximation in models for index option pricing with non mean-zero jumps in prices, non-zero correlation, and jumps in volatility and concludes the bias, for at-the-money options, is negligible. Errors are even smaller here, as the references cited above indicate that the leverage effect is smaller for individual equity than for indices. Since all of our estimators rely on differences between Black-Scholes implied variances, any level biases are differenced out. Thus we conclude that assuming $\left(\sigma_{t,T}^{BS}\right)^2 = EIV_{t,T}$ does not introduce any substantive biases.

Assume that there are two ATM options available at maturities T_1 and T_2 and there is one earnings announcement between time t and $T_2 > T_1$. For generality, consider a square-root SV model with Poisson jumps in variance:

$$dV_t = \kappa_v^{\mathbb{Q}}\left(\theta_v^{\mathbb{Q}} - V_t\right)dt + \sigma_v\sqrt{V_t}dW_t^v(\mathbb{Q}) + d\left(\sum_{j=1}^{\bar{N}_t(\mathbb{Q})}\bar{Z}_j^v(\mathbb{Q})\right),$$

where the shocks are all independent, $\bar{Z}_j^v(\mathbb{Q}) > 0$ with mean $\bar{\mu}_v^{\mathbb{Q}}$, $\bar{N}_t(\mathbb{Q})$ is Poisson process with intensity $\bar{\lambda}_v^{\mathbb{Q}}$ under $\mathbb{Q}$. It is important to note that there is no evidence that the variance for individual equities jumps, however, we include it here for completeness and to understand its potential impact.

Both the term structure and time series estimators rely on differences between the implied variances of two option maturities. To understand how SV affects these estimators, first, compute the expected integrated variance:

$$EIV_{t,T_i} = \widetilde{\theta}_v^{\mathbb{Q}} + \frac{1 - e^{-\kappa_v^{\mathbb{Q}}T_i}}{\kappa_v^{\mathbb{Q}}T_i}\left(V_t - \widetilde{\theta}_v^{\mathbb{Q}}\right), \tag{9}$$

[29]Merton was surprised how small the errors were: "What I did find rather surprising is the general level of the magnitudes of the errors. For the smallest frequency value examined, the percentage of variation caused by the jump component had to exceed forty percent before an error of more than five percent could be generated... In summary, the effect of specification error in the underlying equity returns on option prices will generally be rather small... However, there are some important exceptions...deep out-of-the-money options can have very large percentage errors." (p. 345).

where $\widetilde{\theta}_v^{\mathbb{Q}} = \bar{\lambda}_v^{\mathbb{Q}} \bar{\mu}_v^{\mathbb{Q}} / \kappa_v^{\mathbb{Q}} + \theta_v^{\mathbb{Q}}$. The estimators' accuracy depends on how variable $EIV_{t,T}$ is as a function of T (for the term structure estimator) and t (for the time series estimator). The term structure estimator relies on the difference between Black-Scholes implied variances, $\left(\sigma_{t,T_1}^{BS}\right)^2 - \left(\sigma_{t,T_2}^{BS}\right)^2$. Since volatility jumps merely alter the long-run mean in EIV_{t,T_i}, they have no impact of the term structure estimator above and beyond the mean-reversion term, so they can be ignored. Time-varying volatility can have an impact because $EIV_{t,T_1} \neq EIV_{t,T_2}$.

This implies that there is a predictable difference in expected volatility over, for example, two weeks and six weeks. Independent of any model, this difference is likely minor. As mentioned in the text, since volatility is very persistent, there will be very little difference in forecasts of volatility over the relatively short horizons used here. Moreover, the IV term structure is very flat for both indices (Broadie *et al.* (2007)) and individual firms, which implies that the variation in expected variance over short horizons tends to be small.

In the SV model above, $V_t - \theta_v^{\mathbb{Q}}$, $\kappa_v^{\mathbb{Q}}$, and T_i could each impact the term structure estimator, while realized jumps in volatility and Brownian shocks have no impact. For each of these, the impact will likely be minor. For example, unless there are large volatility risk premiums (for which there is no evidence for individual firms), $\theta_v^{\mathbb{Q}} \approx \theta_v^{\mathbb{P}}$ which implies that, *on average* $V_t \approx \theta^{\mathbb{Q}}$. This further implies biases will be small, at least on average. Since the IV term structure is very flat, even in periods of very high volatility and especially for the shortest maturities, this implies that V_t is close to $\theta_v^{\mathbb{Q}}$ and/or $\kappa_v^{\mathbb{Q}}$ is small. Volatility is also highly persistent and we use short-dated options, implying that $\kappa_v^{\mathbb{Q}}$ and T_i are small and thus the predictable differences in IV over various maturities is small.

More formally, there is some evidence regarding likely parameter values. For index options, Pan finds that $\kappa_v^{\mathbb{Q}} = -0.05$, which implies explosive volatility, but it is not statistically different from zero.[30] Using time series models, Cheung and Johannes (2006) analyze square-

[30] Typical risk premium estimates imply that $\kappa_v^{\mathbb{Q}} < \kappa_v^{\mathbb{P}}$, see, for example, Pan (2002) or Eraker (2004).

root SV models with jumps on EADs. They find that individual firm volatility, once earnings announcements are accounted for, is more persistence than index volatility with estimates of κ_v being around 1.5-3. Since it is typically assumed that $\kappa_v^{\mathbb{Q}} < \kappa_v^{\mathbb{P}}$, this implies a relatively modest level of mean-reversion. In section 4.7, we report estimates of $\kappa_v^{\mathbb{Q}}$ of the order of 1.

The term structure of IVs is also very flat. This is true for both indices and individual equity options. For example, Broadie *et al.* (2007) find that the slope of the IV term structure is less than 1% for S&P 500 options. The same result holds for the firms in our dataset. A flat average term structure indicates that $\theta_v^{\mathbb{Q}} \approx \theta_v^{\mathbb{P}}$ and/or that $\kappa_v^{\mathbb{Q}}$ is small. Further evidence pointing toward mild risk-neutral mean-reversion comes from variation in the slope of the IV term structure for individual options. In addition to little average slope, there is also very little term structure slope even in very high or very low states. For example, Table A.1 shows that for MSFT and INTC the $(5, 95)\%$ quantile of the term structure slope is $(-2.86, 1.40)\%$ and $(-3.44, 1.41)\%$, respectively, pointing to a very low value of $\kappa_v^{\mathbb{Q}}$. Last, most trading volume is concentrated in short-dated options, and we use the shortest maturities for estimation. In practice, we almost always have the two near maturity contracts. Putting the pieces together, this implies that any the impact of mean-reversion is small.

To provide some further intuition regarding the size of the errors, consider the following reasonable SV parameters: $\theta_v^{\mathbb{Q}} = (0.3)^2$, $\kappa_v^{\mathbb{Q}} = 2.5$, and $\sigma_j^{\mathbb{Q}} = 0.10$. Compared to the empirical evidence, this is a high level of mean reversion. Computing the term structure based estimator for $\sqrt{V_t} = (0.20, 0.40.0.50)$, assuming the short-dated option matures in one week (1/52), two weeks (2/52), or three weeks (3/52) and assuming the second option matures one-month later, we have that ${\sigma_j}^{\mathbb{Q}} = (0.0995, 0.1007, 0.1017)$, $(0.0988, 0.1017, 0.1038)$, or $(0.0979, 0.1029, 0.1064)$, respectively. The effect is small as volatility is persistent and option

Jones (2003), like Pan (2002), finds explosive risk-neutral volatility, although its magnitude is small.

maturities are short, implying that $\left(1-e^{-\kappa_v^{\mathbb{Q}} T_i}\right)/\kappa_v^{\mathbb{Q}} T_i$ does not vary a lot across maturities.

Next, consider the time series estimator:

$$\left(\sigma_{t,T_i}^{BS}\right)^2 - \left(\sigma_{t+\Delta,T_i-\Delta}^{BS}\right)^2 = EIV_{t,T_i} - EIV_{t+\Delta,T_i-\Delta} + T_i^{-1}\left(\sigma_j^{\mathbb{Q}}\right)^2,$$

and note that EIV_{t,T_i} is a function of V_t while $EIV_{t+\Delta,T_i-\Delta}$ is a function of $V_{t+\Delta}$. If $V_t \approx V_{t+\Delta}$, then the estimator is quite accurate as the effect of mean-reversion over one-day is negligible. Using the parameters from above, the estimates for three weeks (i.e. the estimator with the largest bias) are ${\sigma_j}^{\mathbb{Q}} = (0.10006, 0.09990, 0.09979)$.

If volatility increases or decreases substantially, the performance of the time series estimator deteriorates quickly, EIV_{t,T_i} and $EIV_{t+\Delta,T_i-\Delta}$ are quite different. Changes in V_t are driven in the specification above by σ_v, the Brownian paths, and $\bar{Z}_j^v$. For the firms in our sample, the volatility of daily changes in volatility is around three to five percent, which implies that normal variation could result in large movements in IV. To gauge their impact, suppose that current spot volatility is 30% and consider a range of changes in volatility on the following day, $V_{t+\Delta} = (0.1, 0.2, 0.25, 0.35, 0.40, 0.50)$. While it is very unlikely that volatility would decrease this much in one day (as jumps in volatility are typically assumed to be positive), we include the lower volatilities to understand the potential impact. For options maturing in three weeks and the same parameters as above, $\sigma_j^{\mathbb{Q}} = (0.1197, 0.1127, 0.1072, 0.0908, 0.0789, 0.0369)$. The potential impact is much larger and, more importantly, is asymmetric: if volatility increases from 30% to 50%, the estimate is biased down by 6.31% while if volatility were to decrease from 30% to 10%, the estimate is biased upward only by 1.97%.

The effect increases with maturity, so that the bias is greater when long-dated options are used. Intuitively, diffusive volatility is more important for long-dated options, magnifying the impact of the shocks. This effect may cause some of the errors we observe, especially if only options with longer maturities are available. For example, if $\sigma_j^{\mathbb{Q}} = 0.05$, the shortest-dated option has 6 weeks to maturity, and V_t increases from 30% to 35%, $\left(\sigma_{t,T_i}^{BS}\right)^2 - \left(\sigma_{t+\Delta,T_i-\Delta}^{BS}\right)^2$ is negative. Long-dated options, combined with close-price issues are, in our opinion, the major cause of the problematic dates for the time series estimator.

Our conclusions are as follows. First, the term structure and time series estimators are generally reliable estimators of $\sigma_j^{\mathbb{Q}}$, even in the presence of SV and/or jumps. Second, the accuaracy of the term structure depends on V_t, $\theta_v^{\mathbb{Q}}$, and $\kappa_v^{\mathbb{Q}}$ and for reasonable parameters, any bias generated is quite small. The performance of the time series estimator depends additionally on σ_v and the realized shocks driving the volatility process. Because of this, the time series estimator is noisier and less reliable than the term structure estimator. Third, for the time series estimator, the magnitudes in the bias are large enough to generate problem dates. Finally, because increases in V_t result in a larger downward bias in estimates of $\sigma_j^{\mathbb{Q}}$ than decreases in V_t (holding the size of increase/decrease constant), the time series estimator will likely have a downward bias if the variance is time-varying or if there are positive jumps in the variance, consistent the empirical estimates.

A.3 Close/open and open/close behavior

We assume that earnings announcements generate a discontinuity in the sample path of equity prices. An alternative assumption is that the diffusion coefficient increases on days following earnings announcements, as in PW (1979, 1981). Thus, the main difference between our model and PW's model is the discontinuity of the sample path. With discretely sampled prices, it is impossible to identify when jumps occurred with certainty. It is common to use statistical methods (see, e.g., Johannes (2004), Barndorff-Nielsen and Shephard (2006), or Huang and Tauchen (2005)) to identify jumps. Identifying jumps on EADs is even more

Table A.1: **Term Structure**

This table provides the average term structure slope calculated as the difference between 30 and 60 days ATM implied volatilities on trading days that are not strongly affected by earnings announcements (we remove all data from 30 days prior to 5 days after an earnings announcement). The columns *High Vol* use only trading dates on which the short-term ATM implied volatility is at least 50% above its average, the columns *Low Vol* use only trading dates on which the short-term ATM implied volatility is more than 30% below its average. The columns *5%* and *95%* provide the 5 and 95% percentiles, respectively.

Firm	All	5%	95%	High vol	5%	95%	Low vol	5%	95%
AMZN	-1.31	-7.01	1.87	0.36	-5.74	8.91	-2.25	-7.76	0.22
AIG	-0.61	-3.72	2.01	-0.94	-6.36	4.26	-0.75	-2.64	0.89
AMGN	-0.54	-4.09	2.31	0.87	-2.73	4.98	-0.95	-4.06	0.43
AAPL	-1.82	-5.93	0.84	-1.05	-5.18	1.97	-1.97	-4.15	-0.05
BAC	-0.52	-2.84	1.50	0.86	-3.53	7.23	-0.63	-2.32	0.59
BA	-0.83	-2.87	1.01	0.68	-4.16	5.68	-0.80	-1.98	-0.07
CAT	-0.97	-3.47	1.52	0.24	-4.84	5.40	-1.41	-3.31	0.04
JPM	-0.03	-2.44	3.03	2.20	-1.63	7.94	-0.63	-2.07	0.50
CVX	-0.08	-1.74	1.78	1.87	-1.23	7.45	-0.51	-1.66	0.22
CSCO	-1.10	-5.27	2.20	0.67	-3.05	3.92	-2.78	-5.95	0.01
C	-0.23	-2.38	2.11	1.19	-1.27	4.53	-0.57	-2.11	0.51
DELL	-1.00	-4.88	2.94	1.44	-2.95	5.93	-1.75	-4.93	0.04
EBAY	-0.96	-4.97	2.53	0.83	-2.63	5.62	-1.81	-4.56	0.01
XOM	-0.20	-1.54	1.06	1.03	-1.01	4.20	-0.51	-1.40	0.09
FCX	-0.24	-2.63	2.67	1.18	-3.42	7.74	-1.15	-2.81	0.13
GE	-0.25	-2.40	2.01	1.34	-1.99	6.22	-0.61	-2.10	0.81
GS	-0.00	-1.95	2.52	2.76	-0.21	11.41	-0.68	-1.61	0.08
INTC	-0.83	-3.44	1.41	0.29	-3.05	3.74	-1.55	-3.37	0.03
IBM	-0.77	-3.00	0.70	0.11	-2.05	2.82	-1.17	-3.04	0.09
JNJ	-0.35	-1.85	0.86	0.60	-0.83	3.73	-0.58	-1.76	0.24
MRK	-0.48	-2.55	1.25	0.51	-0.85	2.42	-1.22	-2.70	-0.03
MSFT	-0.53	-2.86	1.40	0.67	-1.92	4.13	-0.86	-2.93	0.59
MS	1.14	-1.44	5.17	8.85	-1.15	28.63	-0.10	-1.62	1.77
NEM	-0.38	-2.56	1.28	0.81	-0.77	3.53	-2.98	-5.34	-0.21
PFE	-0.40	-2.27	1.64	1.25	-0.35	3.88	-1.12	-2.43	-0.06
MO	-0.42	-3.20	1.70	0.21	-2.17	2.66	-0.91	-3.52	0.25
COP	-0.70	-3.17	1.62	1.31	-2.22	5.24	-1.54	-4.75	0.29
PG	-0.36	-1.96	0.88	0.09	-1.75	1.90	-0.70	-2.53	0.31
QCOM	-0.80	-4.04	1.68	0.70	-4.27	7.15	-1.69	-4.35	-0.02
T	-0.61	-2.11	0.62	0.30	-2.81	3.29	-1.01	-2.34	-0.15
X	0.04	-3.21	4.01	3.11	-2.49	12.15	-2.50	-5.24	-0.42
UPS	-0.23	-1.82	1.12	0.80	-0.39	2.88	-0.49	-2.02	-0.00
VZ	-0.48	-2.32	1.18	0.43	-1.71	2.58	-1.08	-2.74	0.06
WMT	-0.35	-1.97	1.32	0.71	-1.79	4.42	-0.88	-1.93	0.25
WFC	-0.47	-3.55	3.52	2.85	-2.74	12.08	-1.19	-2.67	-0.06
YHOO	-1.07	-5.63	3.56	0.74	-5.32	8.56	-2.20	-5.84	0.30
NFLX	-2.74	-11.58	1.97	2.30	-0.99	6.72	-4.81	-11.74	-0.16
SHLD	-2.37	-7.16	1.44	-5.33	-14.81	0.83	-2.92	-6.76	1.24
GOOGL	-1.22	-5.16	2.34	1.70	-2.63	6.07	-2.81	-5.03	-0.63
MA	-0.91	-5.74	1.56	1.00	-7.15	9.42	-1.14	-3.85	0.00
FSLR	-0.86	-6.58	4.14	4.58	-0.41	11.69	-1.94	-7.16	1.55

difficult in our setting as earnings are announced outside of normal trading hours.[31]

Since it is impossible to ascertain with discretely sampled prices whether or not there is a jump, we consider the following intuitive metric. Strictly speaking, there will almost always be a "jump" from close-to-open, as the opening price is rarely exactly equal to the close price. For example, there are many events that could cause relatively minor overnight movements in equity prices and result in a non-zero close-to-open movement: movements of related equity and bond markets (e.g., Europe and Japan), macroeconomic announcements such as employment or inflation (typically announced at 8:30 a.m. EST, an hour before the formal market open), or earnings announcements of related firms to name a few. The main difference, however, is that if our assumption of a jump on earnings dates is true, the magnitude of the moves should be much bigger for earnings dates versus non-earnings dates. Statistically, the movements should appear as outliers.

To analyze this issue, we compare the standard deviation of close-to-open to returns on announcement and non-announcement days over our sample.[32] Table A.2 provides the standard deviation of close-to-open and open-to-close returns for earnings and non-earnings dates and the ratios comparing earnings and non-earnings dates for all firms with at least 7 years of data. Note first that the results indicate that the close-to-open returns on earnings dates are, on average, much more volatile. Average volatility of close-to-open returns on earnings days was 5.93% compared to 1.59% on non-earnings dates. An F-test for equal variances is rejected against the one-sided alternative at the one-percent critical level for all but two cases for which the p-values are 3% and 6%. Since we usually identify outliers as movements greater than three standard deviations, this is clear evidence of abnormal or jump behavior.

[31] Barclay and Hendershott (2003, 2004) argue that, relative to normal trading hours, after-hour prices are less efficient as bid-ask spreads are much larger, there are more frequent price reversals, and generally noisier in post close or pre-open trading.

[32] We remove days on which dividends are paid from the sample.

Table A.2: **Close-to-open and Open-to-close Return Standard Deviation**

This table provides a comparisons of close-to-open and open-to-close return standard deviation on earnings (EAD) and non-earnings (non-EAD) announcements dates. We provide standard deviations, the ratio of standard deviations and p-values of one-sided F-tests.

Ticker	EAD Close-Open	Non-EAD Close-Open	Ratio	F-Test	EAD Open-Close	Non-EAD Open-Close	Ratio	F-Test
AAPL	6.26	1.47	4.27	0.00	2.46	2.12	1.16	0.05
AIG	3.11	0.91	3.41	0.00	2.15	1.72	1.25	0.02
AMGN	3.71	1.22	3.04	0.00	2.79	2.10	1.33	0.00
AMZN	10.87	1.67	6.51	0.00	5.47	2.89	1.89	0.00
BA	2.61	1.06	2.46	0.00	2.25	1.62	1.39	0.00
BAC	2.61	1.29	2.02	0.00	3.84	1.95	1.97	0.00
C	2.55	0.99	2.58	0.00	1.84	1.55	1.19	0.04
CAT	4.58	1.01	4.55	0.00	2.57	1.68	1.53	0.00
COP	1.31	1.07	1.22	0.06	2.16	1.82	1.19	0.09
CSCO	6.71	1.28	5.23	0.00	2.60	2.20	1.18	0.03
CVX	1.02	0.83	1.23	0.03	1.46	1.44	1.01	0.43
DELL	5.80	1.42	4.08	0.00	2.94	2.37	1.24	0.04
EBAY	7.03	1.46	4.81	0.00	4.87	3.23	1.51	0.00
FCX	2.95	1.78	1.66	0.00	3.12	2.56	1.22	0.02
FSLR	12.57	1.98	6.34	0.00	5.00	3.69	1.36	0.01
GE	2.55	1.11	2.29	0.00	2.75	1.67	1.65	0.00
GOOGL	6.62	0.89	7.43	0.00	2.45	1.53	1.60	0.00
GS	2.97	1.23	2.41	0.00	3.56	1.86	1.92	0.00
IBM	4.40	0.81	5.41	0.00	2.06	1.37	1.50	0.00
INTC	5.18	1.31	3.95	0.00	2.84	2.00	1.42	0.00
JNJ	1.25	0.69	1.81	0.00	1.38	0.99	1.39	0.00
JPM	2.48	1.30	1.90	0.00	2.63	2.22	1.19	0.02
MA	4.76	1.16	4.11	0.00	4.18	2.04	2.05	0.00
MO	1.17	0.83	1.41	0.00	1.59	1.40	1.14	0.10
MRK	2.10	0.97	2.18	0.00	1.62	1.40	1.16	0.08
MS	4.69	2.44	1.92	0.00	3.64	2.86	1.27	0.02
MSFT	5.18	0.92	5.62	0.00	2.29	1.60	1.43	0.00
NEM	1.75	1.09	1.60	0.00	3.19	1.80	1.77	0.00
NFLX	19.50	1.62	12.02	0.00	5.94	2.75	2.16	0.00
PFE	2.69	0.91	2.94	0.00	1.90	1.32	1.44	0.00
PG	2.04	0.84	2.45	0.00	2.22	1.12	1.98	0.00
QCOM	5.70	1.39	4.11	0.00	2.99	2.41	1.24	0.00
SHLD	7.84	1.29	6.06	0.00	5.09	2.74	1.86	0.00
T	1.93	0.75	2.58	0.00	1.57	1.23	1.28	0.01
UPS	1.82	0.60	3.04	0.00	1.97	1.08	1.82	0.00
VZ	1.54	0.74	2.10	0.00	1.82	1.29	1.41	0.00
WFC	5.27	1.79	2.94	0.00	4.01	2.68	1.50	0.00
WMT	2.10	0.69	3.03	0.00	1.16	1.21	0.96	0.64
X	3.70	1.79	2.07	0.00	3.66	3.23	1.13	0.16
XOM	1.46	0.75	1.95	0.00	1.48	1.33	1.12	0.12
YHOO	7.71	1.94	3.97	0.00	3.86	2.80	1.38	0.00
Pooled	5.34	1.25	4.28	0.00	3.00	2.03	1.48	0.00

Second, note that open-to-close returns are slightly more volatile on earnings dates than non-earnings dates, on average 3.00% compared to 2.03% which indicates that returns are slightly more volatile during the day following announcements. This could be due to a number of factors, such as price discovery through trading, liquidity, or inefficient opening procedures. Regarding the last point, Barclay *et al.* (2003) argue that the Nasdaq opening procedure introduces more noise than the opening procedure on the NYSE and the effect is exacerbated for smaller firms.

A.4 Nonparametric Tests: Empirical Results

This section provides further details on the nonparametric tests described in Section 4.2. Table A.3 provides p-values (by calendar year and for the entire sample) for the Wilcoxon and Fisher nonparametric test for our three main hypothesis: (1) IV increases prior to an EAD; (2) the term structure of IV is downward sloping before the EAD; and (3) IV decreases after the announcement. Table A.4 provides the statistical tests on the firm level. A detailed discussion of our empirical results is provided in the main body of the paper (Section 4.2).

A.5 Error Analysis

In this section we study the *error* occurrences in Tables 4 and 6 in more detail. Our main goal is to provide quantitative evidence whether errors can be linked to the presence of SV and other market-microstructure effects. To understand the effect of SV on the likelihood of errors, we first consider the term-structure estimator. It is clear from Equation (4) that a low level of SV would bias $\sigma^{\mathbb{Q}}_{term}$ downward due to the increasing volatility term structure that would result from the mean-reversion of variance. Our model therefore predicts more errors during low volatility regimes. For the time-series estimator, the main driver of errors

Table A.3: **Wilcoxon and Fisher tests (by calendar year)**

This table provides the p-values for the Wilcoxon and Fisher nonparametric test, pooled by calendar year. We use one-sided versions to test the increase in implied volatility in the two weeks prior to an earnings announcement (Increase Prior to EAD), the decreasing term structure of implied volatility before the earnings announcements (Term Structure on EAD), and the decrease in implied volatility after the earnings announcement (Decrease after EAD).

	Increase Prior to EAD		**Term Structure on EAD**		**Decrease after EAD**	
Year	Wilcoxon	Fisher	Wilcoxon	Fisher	Wilcoxon	Fisher
2000	7.29e-20	3.24e-19	2.31e-30	6.23e-43	2.06e-22	4.90e-17
2001	1.54e-11	7.83e-11	1.11e-29	8.95e-42	7.46e-25	5.68e-22
2002	1.59e-16	1.04e-12	3.36e-30	6.09e-41	2.16e-24	2.09e-20
2003	4.52e-10	0.00027	2.02e-26	3.19e-31	1.54e-29	1.35e-39
2004	3.15e-19	3.19e-19	1.56e-20	1.31e-20	5.76e-26	3.88e-37
2005	9.77e-15	4.01e-11	2.12e-23	1.35e-25	6.96e-29	3.95e-31
2006	8.15e-26	3.38e-25	8.44e-33	3.72e-44	1.01e-28	2.57e-35
2007	4.10e-22	1.12e-18	1.09e-31	2.78e-40	4.00e-29	2.78e-40
2008	2.12e-17	1.04e-15	1.26e-31	6.71e-50	1.14e-24	1.89e-32
2009	0.00248	0.12221	7.71e-31	1.79e-42	3.75e-28	7.77e-39
2010	1.05e-08	1.55e-05	2.90e-29	6.22e-31	9.55e-29	2.03e-33
2011	3.34e-14	1.25e-09	4.16e-32	9.90e-39	2.81e-28	1.28e-35
2012	3.12e-23	5.98e-20	6.25e-33	2.53e-46	1.07e-30	3.43e-45
2013	7.43e-29	4.81e-31	1.69e-34	3.22e-54	1.66e-32	4.86e-46
2014	9.34e-23	1.18e-28	2.25e-34	4.98e-60	7.04e-33	3.86e-49
2015	2.06e-15	1.05e-19	1.24e-25	1.57e-41	1.62e-24	8.30e-37
Pooled	1.55e-235	5.69e-191	0.00e+00	0.00e+00	0.00e+00	0.00e+00

Table A.4: **Wilcoxon and Fisher tests (by firm)**

This table provides the p-values for the Wilcoxon and Fisher nonparametric test for all firms with more than seven years of EAD data from January 2000 until August 2015. We use one-sided versions to test the increase in implied volatility in the two weeks prior to an earnings announcement (Increase Prior to EAD), the decreasing term structure of implied volatility before the earnings announcements (Term Structure on EAD), and the decrease in implied volatility after the earnings announcement (Decrease after EAD).

	Increase Prior to EAD		**Term Structure on EAD**		**Decrease after EAD**	
Ticker	Wilcoxon	Fisher	Wilcoxon	Fisher	Wilcoxon	Fisher
AAPL	3.31e-08	3.80e-09	2.65e-10	4.44e-16	2.81e-10	2.31e-14
AIG	0.00095	0.02139	1.83e-07	1.84e-08	1.17e-06	9.71e-07
AMGN	0.21198	0.16200	1.36e-07	9.29e-08	2.27e-07	7.28e-11
AMZN	6.92e-10	8.77e-11	1.84e-11	6.94e-18	5.17e-12	2.19e-16
BA	0.04441	0.27860	5.22e-05	2.82e-06	3.50e-05	0.00076
BAC	3.90e-08	2.86e-08	1.02e-09	1.21e-10	7.48e-05	9.90e-05
C	2.97e-07	4.48e-06	8.75e-09	1.39e-09	0.00217	0.00154
CAT	0.00060	0.00014	1.82e-09	1.42e-14	3.75e-09	1.54e-11
COP	0.52395	0.64945	1.20e-05	9.00e-05	0.00018	0.00046
CSCO	1.23e-11	1.73e-18	8.36e-12	8.67e-19	8.79e-12	5.29e-17
CVX	0.46441	0.24343	0.00096	0.01441	0.00050	0.00567
DELL	0.00028	1.37e-05	2.00e-06	3.73e-09	3.54e-05	1.52e-06
EBAY	0.00028	0.00125	9.13e-07	9.31e-10	9.13e-07	9.31e-10
FCX	0.08249	0.16839	1.25e-08	1.08e-10	1.30e-07	1.08e-10
FSLR	1.20e-05	7.75e-07	4.28e-05	2.09e-07	5.20e-06	2.09e-07
GE	2.44e-07	9.58e-06	8.45e-11	8.62e-15	4.92e-09	1.69e-08
GOOGL	4.04e-07	6.17e-08	5.80e-09	1.14e-13	7.17e-09	5.00e-12
GS	3.17e-09	2.90e-09	6.36e-11	1.55e-15	4.66e-10	4.28e-14
IBM	1.43e-11	4.24e-16	2.65e-12	1.08e-19	4.08e-12	6.94e-18
INTC	3.15e-11	2.82e-12	3.88e-12	2.17e-19	1.36e-11	4.24e-16
JNJ	7.99e-05	0.00299	9.30e-07	9.71e-09	4.22e-06	6.46e-06
JPM	5.56e-09	3.76e-07	2.05e-11	5.95e-14	2.30e-09	9.53e-12
MA	0.00039	0.00077	2.97e-06	7.45e-09	4.65e-06	2.09e-07
MO	0.03858	0.20252	0.16203	0.22569	2.50e-05	2.65e-06
MRK	0.23189	0.50000	6.93e-05	2.11e-05	3.69e-06	4.18e-06
MS	0.00022	0.00016	2.86e-06	2.32e-06	0.00062	0.00016
MSFT	5.52e-07	9.58e-06	3.88e-12	2.17e-19	6.06e-10	8.62e-15
NEM	0.47730	0.42528	0.00222	0.00468	0.00069	0.00046
NFLX	1.06e-05	7.75e-07	2.97e-06	7.45e-09	7.24e-06	2.09e-07
PFE	0.00034	0.00805	4.20e-07	1.23e-08	7.11e-05	2.77e-06
PG	0.00060	0.01785	2.28e-10	3.06e-13	3.08e-08	6.42e-10
QCOM	2.41e-06	1.04e-05	4.08e-12	1.37e-17	4.96e-12	4.24e-16
SHLD	0.00168	0.00732	2.15e-05	2.38e-07	0.00016	7.63e-06
T	0.05037	0.19576	1.15e-06	1.73e-06	3.20e-06	2.09e-07
UPS	0.02985	0.14314	1.79e-05	1.37e-05	6.36e-05	0.00016
VZ	0.24858	0.63583	1.07e-05	0.00016	9.54e-08	5.38e-10
WFC	0.00131	0.00166	6.17e-07	4.66e-10	0.00011	2.31e-07
WMT	3.53e-09	3.80e-09	3.36e-10	5.89e-13	9.58e-09	6.06e-08
X	0.62661	0.50000	9.91e-06	5.25e-06	0.00037	0.00076
XOM	0.06640	0.05864	1.78e-06	2.85e-05	4.00e-07	3.43e-07
YHOO	1.17e-08	8.09e-10	1.24e-09	7.11e-15	7.28e-09	3.41e-13

is expected to be the level of vol-of-vol as higher vol-of-vol adds further noise to the change of IV on EADs.

Our model also predicts that the probability of an error increases for firms with low variance ratios (provided in Table 3). This is because an EAD jump is much easier to identify if the jump size standard deviation is large relative to the average day-to-day variation in returns. Similarly, the signal-to-noise ratio is higher for options with shorter maturities as their annualized return variance is dominated by EAD jump volatility. More errors are therefore expected for estimators based on longer-term options and for firms with a low variance ratio. Another interesting possibility is to test whether the actually reported earnings per share (EPS) affect the likelihood of an error. This is particularly relevant for the time series estimator as it is based on ex-post data. It is intuitively plausible that a lower than expected EPS leads to an increase in the perceived riskiness of the company, hence IV after the earnings announcement may not drop as much as expected or may even increase.

We use a logit model to estimate the impact of aforementioned variables on the likelihood of errors. We measure the volatility as the 30-day implied ATM volatility 10 days prior to the announcement. The vol-of-vol is measured as the standard deviation of 30-day ATM IV changes over 60 trading days prior to the announcement (the last volatility used is 10 days before the EAD). The variance-ratio is defined as in Table 3 and DTM measures the days to maturity of the options used in the calculation of the time-series and term-structure estimator.[34] Finally, the earnings-surprise is given by the actual reported EPS minus the analyst consensus in the month before the announcement, normalized by the equity price ten days prior to the EAD. This definition coincides with DellaVigna and Pollet (2009).

Our findings are reported in Table A.5. We provide two sets of results for each estimator, one with all aforementioned explanatory variables and one with a subset of variables. We

[34]For the term-structure estimator DTM is the maturity of the shorter-term option.

Table A.5: **Error Analysis: Logit Regression**

This table provides results for a logit regression of the occurrences of errors in the time-series and term-structure estimator of Section 2 on a range of explanatory variables. We measure the volatility as the 30-day implied ATM volatility 10 days prior to the announcement. The vol-of-vol (*VolofVol*) is measured as the standard deviation of 30-day ATM IV changes over 60 trading days prior to the announcement (the last volatility used is 10 days before the EAD). The variance-ratio is defined as in Table 3 and DTM measures the days to maturity of the options used in the calculation of the time-series and term-structure estimator.[33] The *earnings surprise* is given by the actual reported EPS minus the analyst consensus in the month before the announcement, normalized by the equity price ten days prior to the EAD.

Estimator	Volatility	VarRatio	Earnings Surprise	DTM	VolofVol
Term Structure Estimator	-5.87	-0.26	9.37	0.02	27.57
	(-7.85)	(-6.45)	(0.55)	(5.18)	(3.35)
	-4.33	-0.27		0.02	
	(-7.80)	(-6.66)		(5.58)	
Time Series Estimator	-0.16	-0.07	1.25	0.01	3.72
	(-0.68)	(-4.17)	(0.30)	(2.99)	(1.01)
		-0.07	1.20	0.01	2.26
		(-4.28)	(0.29)	(2.99)	(0.72)

find broad support for our model predictions and that some of the errors are driven by market-microstructure effects. The signs of DTM and the variance ratio variables are as predicted and highly significant. The sign of the volatility variables is negative for the term structure estimator indicating that lower levels of volatility increase the likelihood of an error. For the time series estimator, we find that higher-vol-of-vol leads indeed to a higher error occurrence, although the parameter is insignificant. Similarly, we find no significant effect of earnings surprises which is reassuring as our estimator does not take into account reactions to earnings announcement news.

A.6 Impact of Stochastic Volatility

It is important to understand how the presence of SV could affect our tests. SV models assume that V_t moves independently of earnings announcements, mean-reverting with random shocks. Thus, even if earnings announcements are important, normal time-variation in volatility could result in either an increase or decrease in volatility prior to an EAD, an increasing or decreasing term structure of IV at an EAD, or an increase or decrease in IV subsequent to an EAD. Thus, SV would introduce additional noise, biasing our tests toward not rejecting, increasing the chances of Type II errors (not rejecting a false null). If, however, anticipated uncertainty plays a dominant role (as Figure 1 would suggest), SV should have a minor effect as the time or maturity variation in EIV_{t,T_i} is swamped by the impact of anticipated uncertainty.

One potential concern is that the increase in IV and the declining term structure of IV prior to earnings could be driven by issues related to expiration cycles: as the time to maturity decreases, option IV tends to increase. There are three reasons this is not a major concern. First, and most importantly, if this is the case, it would have a mixed impact on our tests. While it would bias the pre-earnings increase and term structure test towards rejection, it would have the *opposite* effect on the time series test subsequent to earnings, as the maturity bias would increase IV rather than decrease it. The fact that the time series test of no decrease in IV subsequent to an EAD is rejected, and that the p-values for the decrease are very low, implies that this is not a particularly important issue. Second, none of our conclusions change if we remove all options with a maturity of less than one week.

It is difficult to imagine an alternative to our explanation for the strong predictable behavior in IV. One potential explanation is Mahani and Poteshman (2008), who document that retail investors increase holdings of options on growth firms prior to EADs. If supply is not perfectly elastic, increases in investor demand translate into increases in prices and IV (see also Garleanu *et al.* (2009)). If, for some reason, retail investors were to sell their entire positions the following day (and there is no evidence this occurs), prices and IV would similarly fall subsequent to the earnings announcement. Could the demand of retail investors generate the magnitudes observed in the data? For example, in the Intel example, could retail investor behavior generate the pattern in IVs in the introduction?

We find it implausible that retail investors have such strong impact for three reasons. First, returns on EADs are far more volatile than returns on other dates. This naturally leads to an increase in IV prior to and decrease in IV subsequent to an EAD as shown by our model. Second, retail investors make up a small portion of option market volume (about 10-15% according to Mahani and Poteshman (2008)). Third, while net demand factors are statistically important, it is unlikely that they could explain the large movements in IV around earnings dates. The results in Bollen and Whaley (2004) indicate that net buying pressure of calls and puts significantly impacts changes in IV, but Garleanu *et al.* (2009) find that the magnitude of the effect to be quite small. For the S&P 500 index, doubling open interest in a day increases IV by 1.8%, which is within the bid-ask spread, and they find the impact is smaller for individual firms. We conclude that our results provide strong statistical evidence in support of our reduced-form model and its main implications. Option IV increases leading into earnings announcements, the term structure declines for the first two maturities, and IV decreases subsequent to the earnings announcement.

A.7 Parameter Estimates in Stochastic Volatility Models

This section provides further discussion of the estimates of structural parameters in the stochastic volatility models presented in Section 4.7 (Table 13).

In terms of structural parameters, the estimates of $\kappa_v^{\mathbb{Q}}$ are similar, between 0.52 and 1.70. The corresponding parameters under the $\mathbb{P}$-measure tend to be slightly larger, but smaller compared to values reported for equity indices. This low level of risk neutral persistence is intuitive, especially over our sample period from 2000 to 2015. Volatility was high at the beginning and end, but low in the middle. A high $\kappa_v^{\mathbb{Q}}$ implies that volatility rapidly mean-reverts, which would make it difficult to fit high and low volatility periods with a constant $\theta_v^{\mathbb{Q}}$. For example, since $\theta_v^{\mathbb{Q}}$ is an average of the two periods, when spot V_t is high, a high value of $\kappa_v^{\mathbb{Q}}$ would imply a lower IV for longer dated options. As mentioned in the main body of the paper, the volatility term structure (outside of months with EADs) is quite flat. The only way to fit these periods is to decrease the level of mean reversion.

The estimates for $\theta_v^{\mathbb{Q}}$ imply plausible long-run volatility means. Long-run volatility in SV and SVEJ is roughly similar, decreasing when random jumps are added. The values for σ_v are mainly identified by the time series of variance and from OTM options. The estimates are consistent with prior work but are generally higher than estimates based on time series data only (see the discussion in Broadie *et al.* (2007)). The parameters of the random jump process imply between 1 to 10 jumps per year (with the exception of AMZN for which we estimate a higher jump intensity), with average jump sizes close to zero and jump size volatilities of 3.85% to 13.02%. Interestingly, the number of jumps decreases from SVJ to SVJEJ, often by roughly the number of EADs indicating that some of the EAD jumps may be incorrectly classified as random jumps in these models. Overall, our estimations provide economically plausible parameters.